WEATHER-RELATED NATURAL HAZARDS IN A CHANGING CLIMATE: ENHANCED UNDERSTANDING OF RISK THROUGH SYSTEMS ANALYSIS

by

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Abstract

Weather-related natural hazards cause significant property damage and loss of life in the U.S. and globally. A better understanding of these risks can lead to more informed decision-making regarding risk management and mitigation. This study focuses on risk from floods and hurricanes and the application of systems engineering approaches to enhance the understanding of these risks. Two types of systems analysis methods are primarily used in this study: data analytics and agent-based modeling (ABM).

The first chapter of this dissertation describes the risks associated with weather-related natural hazards and how these risks are typically simulated and managed. The potential effects of climate change are discussed. The second chapter describes a longitudinal study of power outages associated with Hurricane Isaac in Louisiana. This analysis provides insight on how precipitation and storm surge, along with wind, contribute to power outages in hurricanes. The third chapter presents a data analytic study of basin characteristics and unexpected streamflow outcomes in the Mid-Atlantic Region. A model of probability of flood frequency outcome versus watershed characteristics was developed and used to understand which characteristics are associated with low probability flood frequency results. The fourth chapter describes an agent-based model (ABM) of evolving flood risk, with a case study in Fargo, North Dakota. This work focuses on how the interplay between individual and community behavior and stochastic flood outcomes affects community flood risk over time. The fifth chapter provides a summary of this dissertation work, including major contributions and limitations.

ABSTRACT

Overall, this work develops new methods for enhanced understanding of risk associated with hurricanes and floods, and provides insight that can lead to improved management of these risks under current and future climate conditions.

Readers:

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Dr. Seth Guikema

Dr. Benjamin Zaitchik

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Chapter 1 Introduction

Weather-related natural hazards repeatedly result in significant property damage and loss of life in the U.S. and internationally. A better understanding of the risks associated with weather-related natural hazards can lead to more informed decision-making regarding risk management and mitigation. This study focuses on risks from floods and hurricanes and the application of systems engineering methods to enhance the understanding of these risks. These risks are many-faceted problems, and systems approaches can provide new insights and solutions. Two types of systems analysis methods, data analytics and agent-based modeling (ABM), are used in this study to develop novel approaches to enhance the understanding and simulation of risks from hurricanes and floods.

1.1 Floods

Flooding is the most common natural hazard and the third most damaging globally, behind storms and earthquakes (Wilby and Keenan 2012). In the United States, floods cause an average of 140 deaths and $6 billion in damages per year (excluding Hurricane Katrina) (Stedinger 2008). Flooding and floodplain management are subjects that have been long-studied. However, flood damage and flood risk continue to increase in the U.S. and abroad. Climate change is anticipated to result in changes in frequency, intensity, spatial extent, duration, and timing of extreme weather. This could result in unprecedented extreme weather and climatic events, which would significantly impact flood risk (Field 2012).

CHAPTER 1 INTRODUCTION

One of the first steps typically completed in assessing and managing flood risk is flood frequency analysis. Flood frequency analysis methods and uncertainty are discussed in detail in Chapter 3. Flood frequency analysis is often followed by hydraulic modeling to estimate flood elevations at specific locations. These estimates of flood elevations can be used to generate floodplain maps. These methods, while very useful, are prone to uncertainty, provide a limited view of flood risk, and often over or underestimate risk.

Sources of uncertainty in modeling flood risk include future hydrologic events, use of simplified models, economic and social uncertainty, performance of water-control measures, limited observation records, spatiotemporal variability in precipitation and flooding potential, and climate non-stationarity (USACE 1996, Morss 2005). Flood risk management is a "continuous process of adaptive management" which raises challenges for uncertainty analysis. Flood risk is traditionally dealt with by conservative assumptions and rules of thumb such as adding freeboard to a design (Hall and Solomatine 2008), instead of with explicit consideration of uncertainty. Uncertainty is only one component of flood management decisions (Morss 2005), and practitioners may not have the time, budget, or knowledge to complete a complicated analysis of uncertainty.

Community flood risk is typically managed through regulations, insurance, and mitigation projects. Flood mitigation projects can be implemented on a community or a regional basis and may include soft measures like warning systems and evacuation plans and hard measures like levees and dams. These measures are undertaken to reduce property damage and increase public safety. However, poorly planned or executed flood mitigation projects can have unanticipated consequences, such as reduced ecosystem services, and can even result in increased flooding and reduced public safety (Criss and Shock 2001). Furthermore, flood control measures can create more damage by enticing development in marginally protected areas. This creates a cycle of development and structural flood mitigation (Birkland et al. 2003). Consideration of the behavioral aspects of flood risk is crucial to minimizing these negative flood mitigation consequences, particularly when examining the evolution of flood risk over time in a given location.

This study attempts to provide insight into flood risk through two separate approaches. The first is a study of the correlation between watershed characteristics and low probability flood frequency outcomes. The second is a study of how individual behavior, community action, and climate change influence the evolution of flood risk.

1.2 Hurricanes

Another natural hazard of particular significance in the U.S. is hurricanes. Hurricanes impact densely populated areas of the United States, particularly in Florida, the Gulf Coast, and the Southeast, causing extensive damages. Hurricane prone areas in the U.S. are almost five times more densely populated than the national average, and hurricanes account for 8 of the top 10 most costly natural disasters in U.S. history (Frey et al. 2010).

The link between climate change and hurricanes is controversial because highly destructive hurricanes are rare, so it is hard to identify changes in frequency and severity. Population and income factor into hurricane damage trends, so that impacts potentially attributable to climate change are not obvious. According to Mendelsohn et al. (2011), the “historic record may simply not be long enough and clear enough to detect how climate may be affecting hurricanes”. Climate change could potentially impact hurricane frequency, intensity, rainfall amounts, and track distribution (Mendelsohn et al. 2011, Knutson 2010). These potential impacts on hurricanes could lead to significant changes in hurricane risk.

Factors impacting hurricane losses include frequency and severity of storms, which can be affected by natural climate variability as well as anthropogenic climate change. Hurricane losses are also dependent on vulnerability and exposure of communities. Factors such as population, per capita assets, settlement and industrialization of exposed areas and location of cities determine vulnerability and exposure. U.S. hurricanes provide heavy losses due to the high concentration of property value in vulnerable areas such as Florida and the Gulf Coast states. Because of this high property value concentration in vulnerable areas, U.S. hurricanes account for a large portion of the worldwide disaster losses (Schmidt et al. 2009).

One of the more costly impacts that hurricanes cause is damage to power systems. Power outages from hurricanes result in direct repair and restoration costs for utility companies, and can also result in loss of services from other types of critical infrastructure that rely on power service such as water, transportation, and communications systems. This can delay recovery times for a community that is impacted by a hurricane (Han et al. 2009). Accurate predictions of power outages prior to a storm can benefit both utility companies and government agencies by making planning and recovery more efficient (Nateghi et al. 2013). To provide insight into hurricane power outage risk, Chapter 2 looks at various drivers of power outages and how they can vary geospatially during a storm.

1.3 Systems Approaches

Risks associated with hurricanes and floods are many-faceted problems, and systems approaches can provide new insights and solutions. Two types of systems analysis methods are primarily used in this study: data analytics and agent-based modeling (ABM).

Data Analytics, or statistical learning, is a set of tools used to understand complex data sets. It generally involves building a statistical model to predict an output variable in terms of a set of input variables. As the field of "big data" expands, the use and applications of data analytics continues to increase (James et al. 2013). Management of risks associated with natural hazards is one of the many fields where data analytics can provide valuable insight.

An agent-based model (ABM) is a stochastic simulation model that includes decision-making entities (agents) in addition to stochastic elements (Bonabeau 2002, Evans 2004, Epstein 2006). An ABM allows for spatially-explicit, heterogeneous agents together with stochastic elements such as flooding events. Agents in an ABM have learning rules that represent how they incorporate new information such as events (e.g., floods) occurring in their environment as well as messages from other agents. They also have decision rules that specify the actions they can choose and how they choose among their possible actions. ABMs have been widely used to examine situations in which individual behavior is an important driver of collective outcomes in ways that cannot be easily modeled by more aggregate models such as system dynamics models. Chapter 4 provides a more detailed background on ABMs, including common uses and limitations.

1.4 Overview

This dissertation consists of three separate studies each involving innovative approaches for analysis of risks from hurricanes and floods. The main research question for each is as follows.

1. Hurricane Isaac Power Outage Analysis – Hurricane power outage prediction models typically focus on wind hazards, but other storm characteristics such as precipitation and storm surge may be significant as well. Which storm characteristics are most strongly correlated with power outages, and how does this correlation vary geographically?

2. Basin Characteristics as Risk Factors for Unexpected Flood Frequency – Standard flood frequency analysis methods are valuable and widely used to establish streamflow probabilities, but due to uncertainty in data and methods, outcomes judged to have a low probability of occurrence by standard flood frequency analysis methods can occur. I hypothesize that statistical analysis can be used to identify watershed characteristics and characteristics of stream gages' peak flow records that are correlated with low probability streamflow outcomes, helping risk analysts and flood risk managers better understand when standard methods are likely to be less accurate.

3. An Agent-Based Model of Evolving Community Flood Risk – Flood risk management and mitigation decisions are often made based on hydrologic and hydraulic (H&H) models and do not consider the influence of individual behavior, policy, and climate change on flood vulnerability. How does individual behavior affect the evolution of community flood risk in conjunction with community interventions and climate change? Can we model the interactions between these drivers by using an agent-based model in combination with physical hazard data?

Chapter 2 Hurricane Isaac Power Outage Analysis[1]

2.1 Introduction

Hurricane Isaac hit Louisiana in August 2012 and caused substantial power outages. It was a Category 1 hurricane at landfall and 47% of the state's electric customers lost power. The storm was large, slow-moving, and had significant storm surge associated with it. In comparison with other hurricanes, Isaac ranks fourth in customer power outages, behind Hurricanes Katrina, Gustav, and Rita, for the Entergy service area in Louisiana, Mississippi, Texas and Arkansas (Chicago Tribune 2012). The track of the storm is illustrated in Figure 2.1 (NHC 2015).

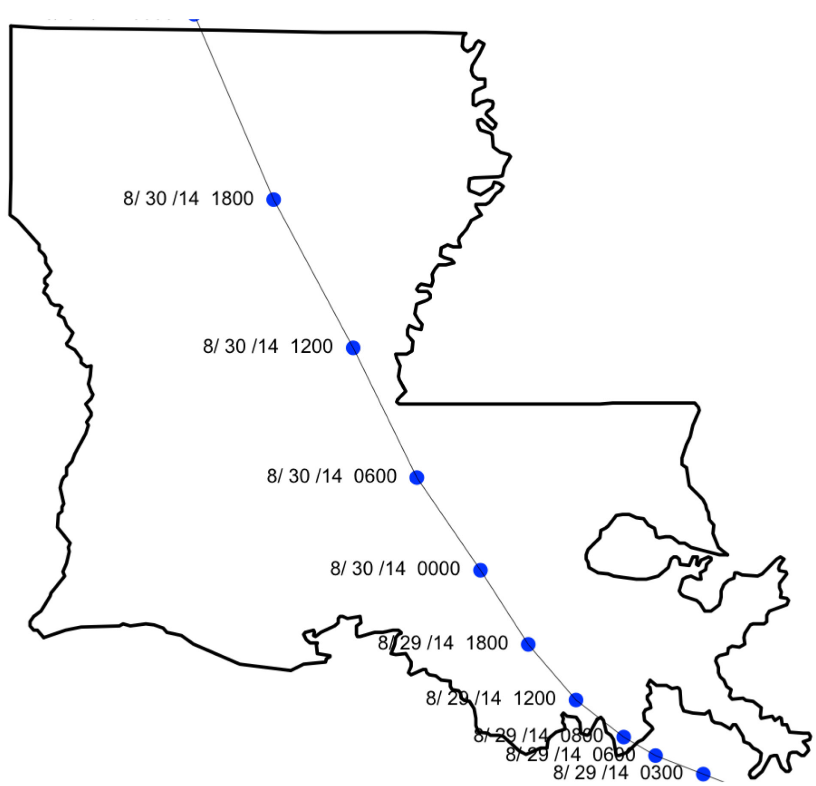

Fig. 2.1 Hurricane Isaac Track

[1] This chapter was published in the journal *Risk Analysis* (Tonn et al. 2016)

CHAPTER 2 HURRICANE ISAAC POWER OUTAGE ANALYSIS

Power outages result in direct repair and restoration costs for utility companies, and can also result in loss of services from other types of critical infrastructure that rely on power service such as water, transportation, and communications systems. This can delay recovery times for a community that is impacted by a hurricane (Han et al. 2009). Accurate predictions of power outages prior to a storm can benefit both utility companies and government agencies by making planning and recovery more efficient (Nateghi et al. 2013).

Power outage prediction is often accomplished through the development of models based on wind field estimates, along with other covariates such as power system data, soil moisture levels, land use and topographical indicators (Nateghi et al. 2013). A number of such statistical models have been developed (Han et al. 2009a, Nateghi et al. 2013, Guikema et al. 2013). While these models can be very accurate for some storms, they are less accurate for others due to the differing characteristics of the storms.

In addition to accuracy of models varying from storm to storm, the causes of the outages can vary geographically across a region, and the existing models typically do not include some potential causes of power outages, particularly heavy rainfall. The main goal of this study is to obtain a better understanding of how storm characteristics correlate with power outages and how this correlation varies geographically. The purpose of this study is both to improve basic understanding of hurricane power outages and to provide a stronger basis for improving outage forecasting models. Are the outage drivers the same for a coastal area as an inland area? How important are rainfall and surge relative to wind? Damage to power systems is recorded by utilities, but good data on causes of outages are not generally available, making a longitudinal approach necessary. Statistical analysis of power outage data and covariate data is used in this analysis to provide a better understanding of how storm conditions correlate with power outages. Power outages were studied longitudinally across the state of Louisiana for Hurricane Isaac to identify how the importance of covariates changes geographically. The results of this analysis may inform power outage prediction models and help to build more resilient infrastructure through improved understanding of power outage risk.

In Section 2.2, the data used for the analysis as well as the statistical analysis methods are presented. Results and Discussion are included in Section 2.3, and Conclusions in Section 2.4.

2.2 Methods and data

This study focused on covariates related to three key physical hazards associated with hurricanes: wind, storm surge, and rainfall, in order to gain a better understanding of the relative contribution of these three storm characteristics. All covariates were analyzed on an hourly basis, and so included covariates that change over time as the storm progresses. Data was obtained for the covariates of interest from publically available sources or modeled based on publically available data. A summary of the covariates, data sources, and a description of each covariate are provided in Table 2.1. While data were available in varying time increments for each covariate, we performed interpolation to obtain hourly estimates. We chose the hourly change in outages as the response variable, and hours that did not have a positive increase in outages were removed from the analysis to focus the analysis on only the outage occurrence portion of the storm, not the outage restoration part of the storm. A more detailed description of each category of data and the data interpolation is provided in Sections 2.2.1 through 2.2.5.

Table 2.1 Summary of Covariates

Category	**Covariate**	**Source**	**Description**
Precipitation	Cumulative Precipitation	National Climatic Data Center (NCDC)	Total precipitation amount during storm duration to hour of analysis in centimeters
	Hourly Precipitation Total	NCDC	Precipitation amount in hour of analysis in centimeters
Wind	Wind Speed	Wind model	Wind speed in meters/second for zip code in hour of analysis
	Wind Gust Duration	Wind model	Duration of wind gust >20 meters/second for zip code in hour of analysis
Outages	Previous Outages	Entergy website	Number of outages in previous hour of analysis for zip code
Population	Population	US Census Bureau	Population estimate for zip code
Surge	Average Surge	ADCIRC+SWAN models	Average storm surge depth for zip code in hour of analysis in meters
	Minimum Surge	ADCIRC+SWAN models	Minimum storm surge depth for zip code in hour of analysis in meters
	Maximum Surge	ADCIRC+SWAN models	Maximum storm surge depth for zip code in hour of analysis in meters
	Surge Variance	ADCIRC+SWAN models	Variance of storm surge depth for zip code in hour of analysis in meters

Initial analysis was done on a statewide basis, with the remainder of the analysis done on a zip code basis. After completing the data collection and interpolation, we generated a Random Forest model for the entire data set including all zip codes. The most important covariates were identified through Random Forest based importance measures for use in additional analysis as described further below. Using this reduced set of covariates, we trained a Random Forest model for each zip code separately so that impacts could be analyzed spatially. We plotted the results in map format for analysis of spatial trends. We used a Quantile Regression Forest model for selected zip codes to gain insight into model accuracy. The modeling and analysis methods are described in more detail in Sections 2.2.6 and 2.2.7.

2.2.1 Outage Data

Power outage data were harvested from the Entergy Louisiana website during the duration of the storm from August 27 to September 5, 2012 (Entergy 2012). The data were collected on a half-hourly basis during periods of peak outages, and were collected less frequently during non-peak outage periods. Data collected included the number of current customer outages by zip code. In order to standardize the data for use in analysis, we performed linear interpolation to estimate the number of outages for each zip code at the top of each hour for the duration of the storm. Some areas of Louisiana are not serviced by Entergy and were not included in this analysis.

We chose the change in outages (termed delta outages in this paper) for each hour of analysis for each zip code as the response variable for this analysis. Total power outages for the previous hour of analysis (Previous Outages) for each zip code was included as a covariate to account for the fact that the number of customers already without power impacts the number of power outages occurring in a given hour.

2.2.2 Precipitation Data

Precipitation data were obtained from the National Climatic Data Center (NCDC) website. Data were available for 36 rainfall stations in Louisiana. The time intervals at which the precipitation data were recorded varied by station, but were typically hourly or half-hourly. The data obtained were the hourly total rainfall (NOAA 2012). In order to standardize the data for use in analysis, we interpolated the data set to estimate the hourly precipitation (precipitation that occurred in the previous 60 minute period) at the top of the hour for each station. Because our analysis was performed on a zip code basis, we needed rainfall estimates for each zip code. Based on the geographic coordinates of the zip code centroids and on the locations of the stations, we generated hourly rainfall estimates for each zip code using inverse distance weighted interpolation based on the spatially sparser set of rainfall stations that were available.

2.2.3 Storm Surge Model

We used the coupled version of the 2-Dimensional Depth Integrated version of the Advanced Circulation (ADCIRC) model and the wave model SWAN (Dietrich et al. 2011) to simulate hurricane storm surge. The ADCIRC model (Luettich and Westerink 2010) is a finite element, shallow water model that solves for water levels and currents at a range of scales and is widely used for storm surge modeling (e.g., Ferreira et al. 2014). This version of the program solves the Generalized Wave Continuity Equation (GWCE) and the vertically integrated momentum equations. SWAN is a third generation spectral wave model (Booij et al. 1999) that computes the time and spatial variation of directional wave spectra. We used the pre-validated numerical mesh *SL15* presented in Bunya et al. (2010) and validated by Dietrich et al.(2010) with resolution up to 30 meters in some areas. The hurricane surge model was forced by wind and pressure fields developed by a parametric asymmetric wind model (Mattocks and Forbes 2008) that computes wind stress, average wind speed and direction inside the Planetary Boundary Layer (PBL) based on the National Hurricane Center (NHC) best track data (NOAA 2013) meteorological conditions (e.g., central pressure, forward speed and radius to maximum wind). The simulations for Hurricane Isaac included tides (Tidal potential components M2, S2, N2, K2, K1, O1 and Q1) and neglected rivers inflows. Simulation results were recorded at 15-minute intervals for every model node in the study region. The water levels for each model node within each zip code were extracted from the entire model domain and inundation levels were converted to the NAVD88 vertical datum. Covariates based on the storm surge model include average storm surge, maximum storm surge, minimum storm surge, and storm surge variance.

2.2.4 Wind Model

The parametric wind field model of Willoughby et al. (2006) was used to generate wind estimates for the duration of the hurricane at the zip code level for Hurricane Isaac. Parametric hurricane models are formulated from a physical understanding of hurricane wind fields. That is, winds are calm in the eye of the hurricane and they are typically at a maximum in the eyewall. Outside the eyewall the wind decreases with radius, although not always monotonically, and becomes near zero at some distance from the center of circulation. This wind field model was previously used in Han et al. (2009a, 2009b). Two of the covariates are based on output from this model. The first is maximum wind speed in meters per second in the previous hour. The second is wind gust duration greater than 20 meters per second, with duration being taken cumulatively over the life of the storm for each zip code. Both of these covariates are simulated for the centroid of each zip code polygon based on running the wind field model every 60 minutes over the duration of the storm.

2.2.5 Other Data

Population estimates for each zip code were obtained from the US Census Bureau American Community Survey. These estimates were based on the US Census Bureau data for the year 2011. Because the US Census bureau does not track population on a zip code basis, the population data are estimates based on census tract data (US Census Bureau 2013).

2.2.6 Random Forest and Quantile Regression Forest Methods Overview

A Random Forest is a non-parametric ensemble data mining method (Hastie et al. 2001). In the method, a large number of regression trees are developed, with each tree based on a bootstrapped sample of the data set. Random Forest models are good for data sets with non-linear data, outliers, and noise. Two types of output from the Random Forest model fit very nicely with the objectives of this analysis. The first is variable importance, which is a measure of the contribution of a given covariate to the model prediction accuracy. The second is the partial dependence plot. These plots show the marginal effect of a covariate on the response variable. The randomForest package in R was used for this analysis (Liaw and Wiener 2002).

Quantile Regression Forests provide a non-parametric way of estimating conditional quantiles based on an underlying Random Forest model. Quantiles give more information about the distribution of the response variable as a function of the covariates than just using the conditional mean as a standard Random Forest model does. In this method, regression trees are grown as in the Random Forest method. Then the weighted distribution of the observed response variables is used to estimate a conditional distribution. The difference between Random Forest models and Quantile Regression Forest models is that Random Forest models keep only the mean predictions and disregard other information. Quantile Regression Forests estimate the quantiles of the predictions based on the trained forest (Meinshausen 2006). The quantregForest package in R was used for this analysis (Meinshausen 2012). Predictions made using this package are based on out-of-bag data generated through the standard random forest bootstrapping process (Liaw and Wiener 2002).

2.2.7. Statistical Analysis

A statewide Random Forest model was run using the data for all covariates and zip codes. Only positive delta outages were included, to limit the analysis to the occurrence of power outages, not the restoration of power. In order to better understand the predictive accuracy of the Random Forest model, a Quantile Regression Forest model was run on ten selected zip codes. The zip codes were chosen so that different geographic areas in the state were represented.

Variable importance was reviewed to identify the variables that were most significant for predictive accuracy. Based on the variable importance, one covariate from each category of covariates (precipitation, wind, storm surge, and outages) was retained for individual zip code analysis in order to better understand the influences of the different variables. Partial dependence plots were generated for each of these covariates, and were reviewed to understand the marginal effects of these covariates on the response variable.

In order to understand the relative importance of the four covariates, and how that importance varied geographically, plots of importance for each of the covariates were generated. Because the magnitude of variable importance was not the same for each Random Forest run, comparing the variable importance between zip codes would not be useful. Instead, we calculated a percent variable importance for each zip code. The variable importance for the four covariates (wind speed, cumulative precipitation, maximum storm surge, and previous outages) was summed to calculate the total importance value for each zip code. Then the percent of total importance accounted for by each covariate was calculated. For each of the four covariates, we plotted the percent variable importance by zip code. We visually reviewed these plots to identify how the percent importance for each covariate differed geographically. The plots were also evaluated in light of the plots of the covariate values, so that the magnitude of the covariates was accounted for in evaluating the percent importance trends.

2.3. Results and Discussion

2.3.1. Quantile Regression Forest

We ran a Quantile Regression Forest model on ten selected zip codes in order to better understand the predictive accuracy of the Random Forest model. These zip codes were selected to cover the geographical range of the state and to include zip codes with varying numbers of outages. Plots of the Quantile Regression Forest results for three zip codes are shown in Figure 2.2. These plots show the 80% prediction confidence intervals and whether predictions using out-of-bag data fall inside or outside of the prediction intervals. As shown on the plots, the majority of the predictions fall within the prediction intervals.

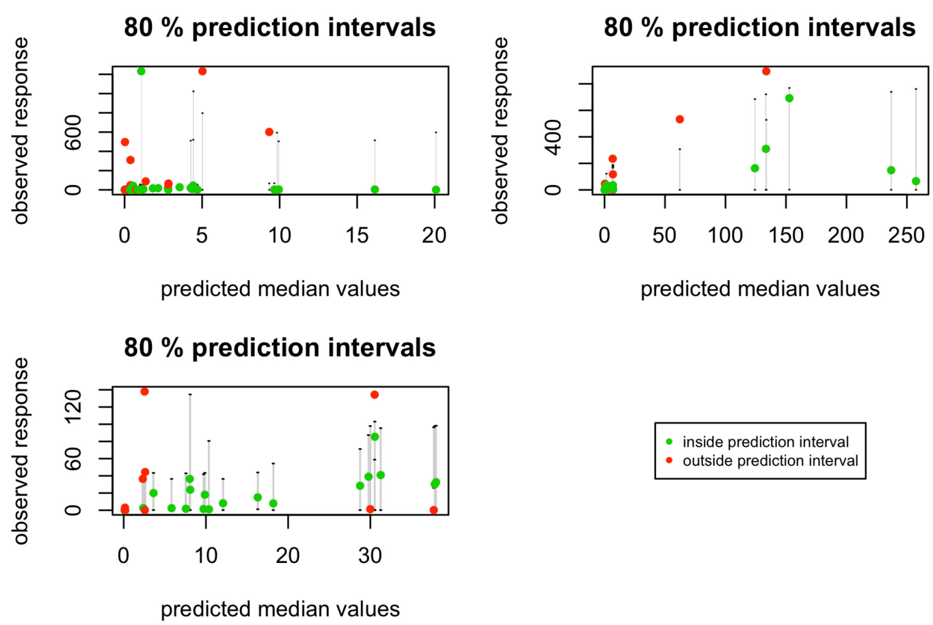

Fig. 2.2 Quantile Regression Forest plots for a) zip code 70129, b) zip code 71220, and c) zip code 70546

Table 2.2 shows the percent of predictions that fall between the 10% and 90% quantiles for the ten zip codes analyzed using the Quantile Regression Forest model. The percent coverage (percent of predictions within the 80% confidence interval) was calculated for three ranges of delta outages: low (0 to 2), medium (2 to 75), and high (75 and above), so that we could understand how the predictive accuracy varied across a range of values. In some cases, no prediction values fell within the low or high range, and this is indicated with an N/A in Table 2.2. The model predictive accuracy is poor within the low range, except for in one zip code. In the medium and high range, the predictive accuracy is generally good, with the exception of predictions for two zip codes in each range. None of the zip codes have a high coverage of the 80% interval throughout the low, medium, and high ranges. However, six of the zip codes have high coverage (75% or greater) in two of the ranges.

For low values of delta outages (0 to 2), four of the zip codes did not have values in this range. With the exception of two zip codes, the coverage of the 80% interval is very low; the model has little reliability at the lowest level of delta outages. For middle of the range values of delta outages (2 to 75), the model confidence interval coverage is fairly high for eight of the zip codes, ranging from 69% to 100%. However, the other two zip codes had only 20% and 39% of predictions within the 80% confidence interval. At the high end of the delta outages range (75+), the coverage accuracy varies significantly. This makes sense given the nature of power outages and the covariates used in the model. Very low increases in power outages are not likely well correlated to storm characteristics, and are more likely caused by random events occurring at individual houses. Very high increases in power outages can sometimes be correlated with high precipitation or wind, but could also occur due to sudden problems in the power grid.

Table 2.2 Percent of Predictions within 80% Confidence Interval

			Delta Outage Range		
Zip Code	**Region**	**Maximum Outages**	**Low (0-2)**	**Medium (2-75)**	**High (75+)**
70129	Southeast	3,364	0%	88%	57%
70454	Southeast	11,314	N/A	100%	96%
70546	Southwest	356	0%	100%	N/A
70560	South	1,684	3%	39%	50%
70607	Southwest	415	N/A	75%	100%
70806	South	11,616	N/A	100%	100%
71055	Northwest	367	N/A	100%	83%
71070	West	437	88%	69%	N/A
71220	North	2,896	3%	76%	100%
71351	East	3,314	100%	20%	96%

Given the low percentage of predictions within the 80% confidence interval for several analyzed zip codes, we decided to investigate whether changing the data set from including all positive delta outages to only delta outages greater than one would increase predictive accuracy. Table 2.3 shows this comparison. Increased percent predictions within the 80% confidence interval occurred for nine of the zip codes, while a slight decrease was observed in zip code 71351. Based on this marked improvement, we decided to include only delta outages greater than one for the remainder of the analysis. This created a more accurate model, without reducing functionality, since prediction of very low delta outages (<1) is unnecessary.

Table 2.3 Percent of predictions within 80% confidence interval, Delta Outages greater than 0 versus greater than 1

	Percent Predictions within 80% Confidence Interval	
Zip Code	**Delta Outages 0+**	**Delta Outages 1+**
70129	59%	85%
70454	96%	96%
70546	65%	100%
70560	24%	74%
70607	82%	100%
70806	100%	100%
71055	96%	100%
71070	73%	91%
71220	75%	100%
71351	69%	67%

2.3.2. Variable Importance

The variable importance results for the Random Forest model with all covariates included are shown in Figure 2.3. Variable importance is a measure of the contribution of a given covariate to the model prediction accuracy, and the magnitude of the importance is based on the data set. In Figure 3, the variable importance is presented as the increase in node purity resulting from splitting over each variable, averaged over all trees. Cumulative precipitation, wind speed, and previous outages are the most important variables, followed by population and hourly precipitation. All of the surge variables, along with wind gust duration, had considerably lower variable importance. This differs from some previous work where wind gust duration was shown to be an important variable (e.g., Han et al. 2009b) and may be specific to this hurricane for which wind speeds were lower than in the hurricanes included in the Han et al. work.

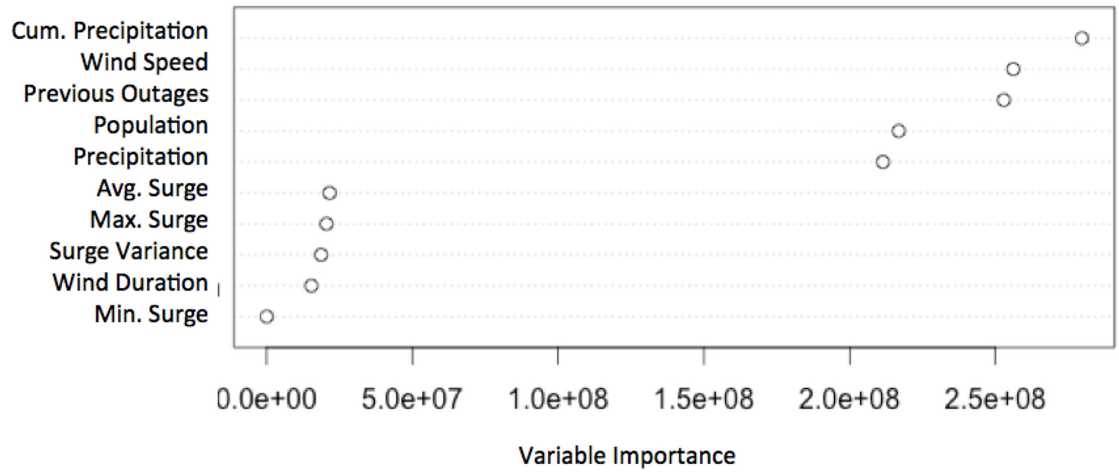

Fig. 2.3 Variable Importance, all covariates included

Based on these results, four covariates were selected as part of a reduced covariate set to be used for the remainder of the analysis. These covariates were: cumulative precipitation, wind speed, previous outages, and maximum surge. Maximum surge depth was selected over average surge depth in each zip code because it had a clearer physical interpretation than the average surge depth yet had nearly the same importance score. Population was not included because the remainder of the analysis was done on an individual zip code basis wherein population is constant. The Random Forest model for the entire state was rerun with this reduced set of covariates. The resulting variable importance plot is included as Figure 2.4. In this model, the cumulative precipitation covariate has the highest variable importance, followed closely by previous outages and wind speed. Maximum surge has a lower importance, as should be expected since only a small portion of the state was impacted by storm surge.

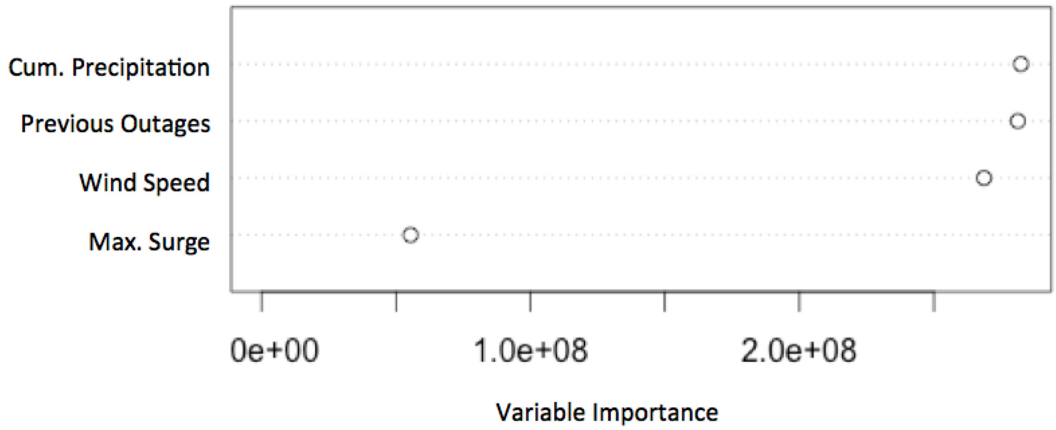

Fig. 2.4 Variable Importance, reduced covariate set

2.3.3. Partial Dependence

Partial dependence plots were generated for the four covariates in the reduced set, and are provided as Figure 2.5. Partial dependence provides insight into the marginal impact of the covariate on the response variable, increase in outages.

The marginal influence of the cumulative precipitation covariate is highest for about 0 to 10 centimeters (cm) of precipitation. This is primarily due to the timing of the storm, with the highest values of delta outages generally occurring in the earlier part of the storm. Cumulative precipitation continued for days after the initial power outages occurred, with limited number of power outages occurring later in the storm. This resulted in a higher marginal influence for lower values of cumulative precipitation. Additionally, only a small percentage of zip codes experienced the highest cumulative precipitation totals (30+ cm). The marginal influence of wind speed generally increases with increasing wind speed, which is intuitive. The influence of maximum surge is more variable, which may be due to the fairly low number of zip codes that experience storm surge. The influence is higher at lower values of surge, likely because few zip codes experienced maximum surge values above 5 meters. The marginal influence of the previous outages covariate increases up to around 10,000 outages, and then slightly decreases, since once a high number of outages occurs in a zip code, additional outages may be small in magnitude, as most customers have already lost power.

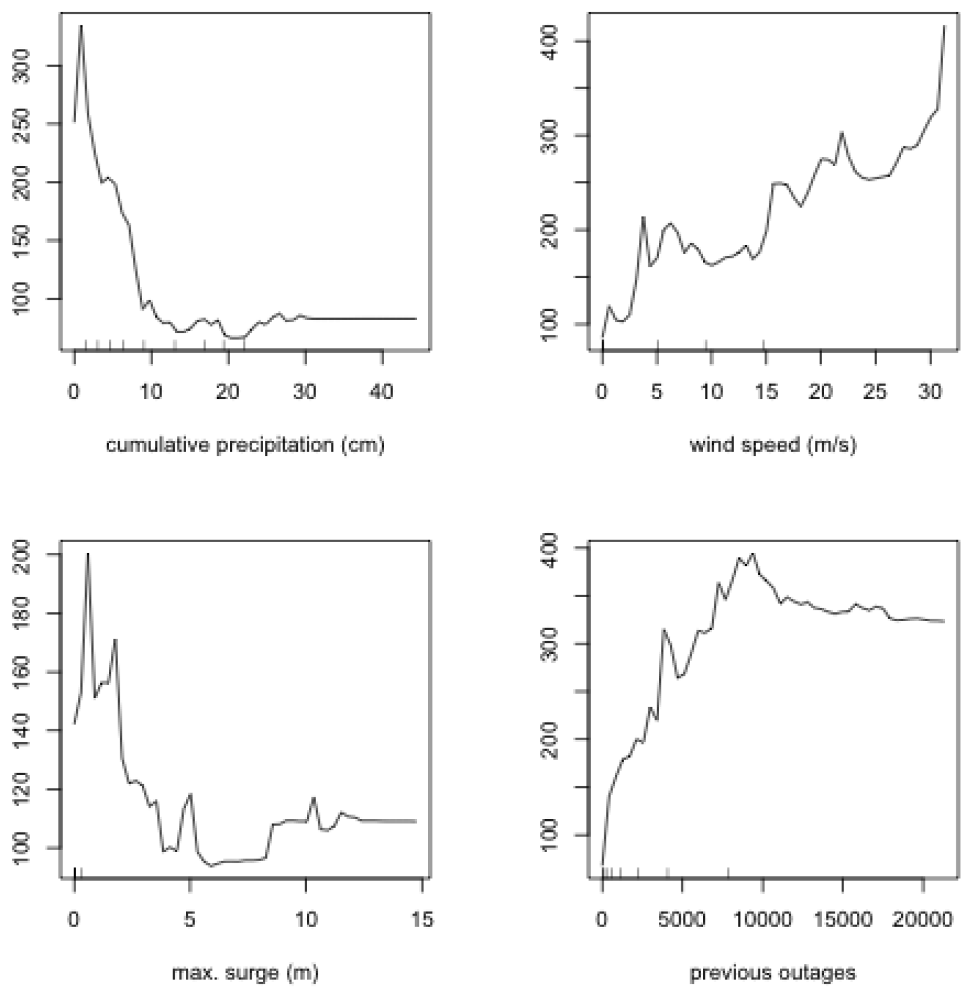

Fig. 2.5 Partial Dependence Plots: a) partial dependence on cumulative precipitation, b) partial dependence on wind speed, c) partial dependence on maximum surge, and d) partial dependence on number of previous outages. The x-axis represents the value of the covariate and the y-axis represents the marginal influence of the covariate on delta outages.

2.3.4. Geospatial Analysis

In order to analyze spatial trends across the state, we generated plots to get a sense of the magnitude of precipitation, wind speed, storm surge, and outages, and how the magnitude varied across the state. These plots are presented as Figure 2.6. Total precipitation (cumulative precipitation) was highest in the southeastern part of the state, with more than 30 cm of precipitation recorded in some locations. Maximum wind speed was also highest in the southeastern part of the state, where the hurricane made landfall. Maximum storm surge was highest in zip codes bordering the Gulf of Mexico, as well as in several zip codes bordering the Mississippi River. The maximum numbers of power outages were observed in zip codes in the southeast, around New Orleans, where the population is greatest and the storm impacts were more pronounced.

Figure 2.7 illustrates the relative importance of cumulative precipitation, wind speed, maximum storm surge, and previous outages for all zip codes analyzed in Louisiana. In the northern part of the state, both cumulative precipitation and previous outages had high relative importance. Moderate amounts of precipitation occurred in this area, while wind speeds and total number of outages in the northern zip codes were lower than in other parts of the state. In the east central part of the state (Baton Rouge area), moderate to high precipitation, winds, and outages were experienced. Wind speed generally had the highest importance in this region, but precipitation and previous outages were also important. In the southeast (New Orleans area), high wind speeds, precipitation, and outages occurred. Precipitation and previous outages had the highest importance in this region, and wind speed was also of importance. In the southwest and south central portions of the state, low to moderate precipitation and winds were experienced. High storm surge occurred in some coastal zip codes. The overall number of outages was low in most zip codes in this region, and the relative importance of each covariate varied considerably by zip code.

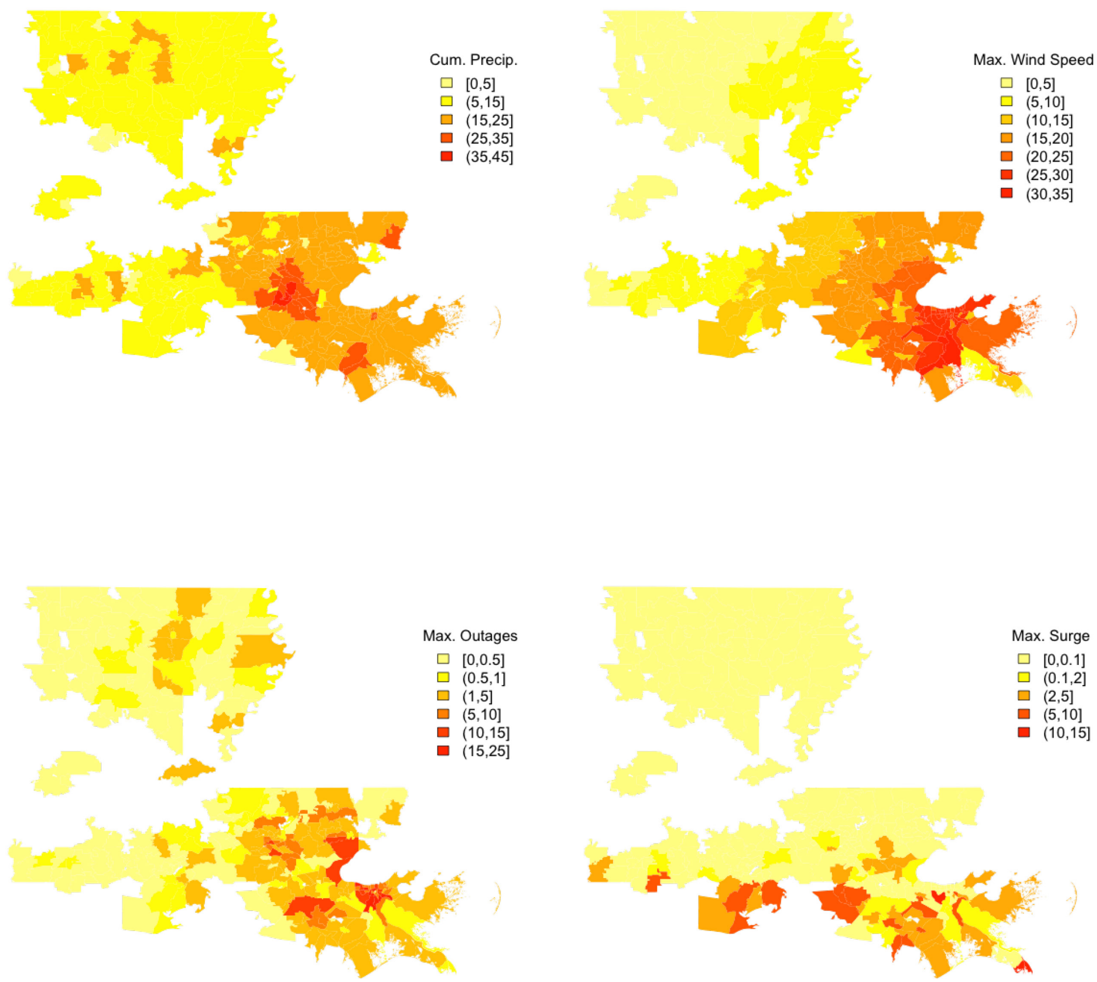

Fig. 2.6 Covariate values for a) cumulative precipitation (cm), b) maximum wind speed (m/sec), c) maximum surge (m), and d) maximum number of outages (thousands). Zip codes not colored are not part of the utility's service area.

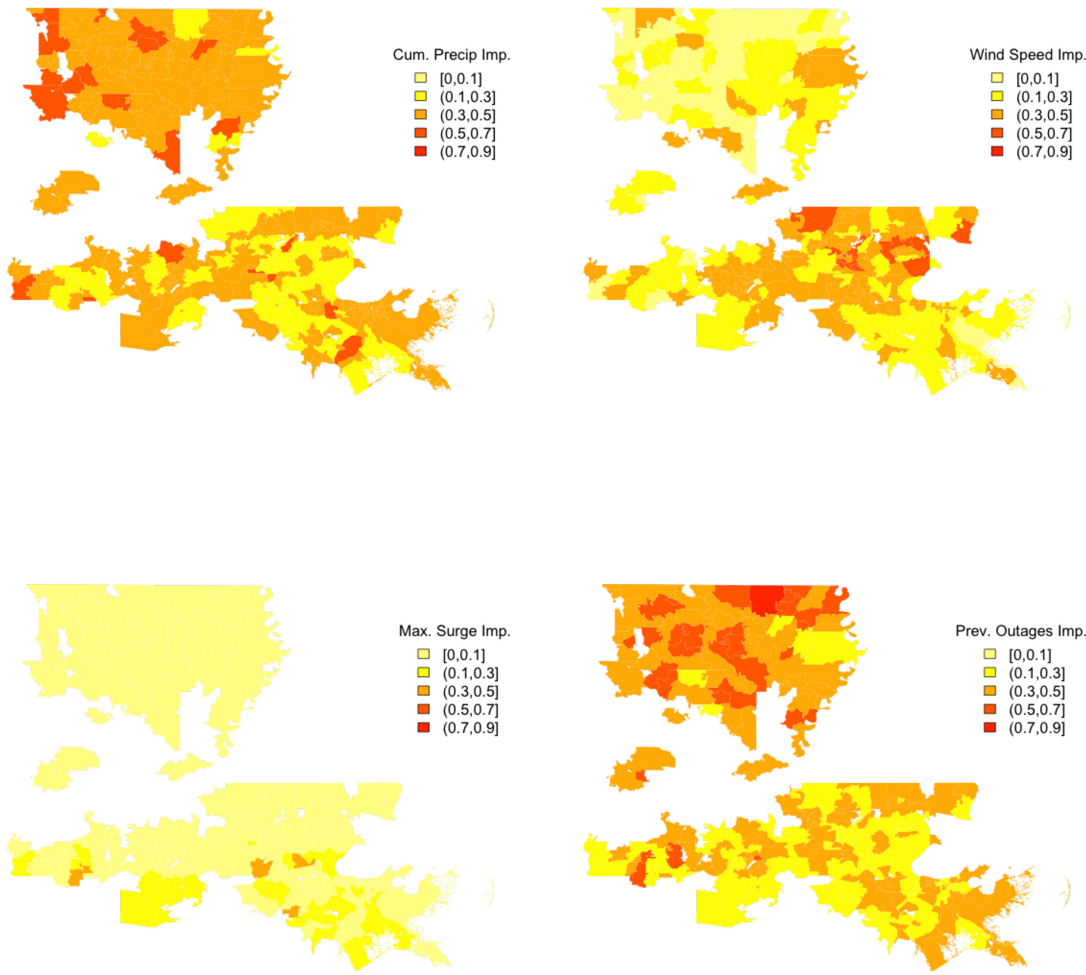

Fig. 2.7 Percent Importance Plots for a) cumulative precipitation, b) wind speed, c) maximum surge, and d) previous outages

Cumulative precipitation was of moderate to high importance in most zip codes throughout the state, including those with relatively low precipitation. Conversely, wind speed generally only had high importance in areas that experienced high wind speeds. With the exception of a few zip codes, the percent importance for maximum storm surge was less than 30%, even in coastal areas. The relative importance of previous outages was moderate to high in most zip codes, and the maximum number of outages in a zip code does not seem directly related to the importance of previous outages in that zip code.

These results indicate that the importance of covariates varies geographically. This is due to the storm's track and characteristics, but also potentially due to the interaction of other factors pertaining to topography and power system. Both wind speed and cumulative precipitation were highest in the east central and southeastern part of the state, due to the storm's track; however, wind speed generally had greater importance in those areas than precipitation. In the northern part of the state, where precipitation was moderately high, but wind speeds were low, precipitation was of greater importance. The previous outages covariate was generally more important in areas that had a low to moderate maximum outages value.

2.4. Conclusions

The purpose of this analysis was to provide insight on how rainfall and storm surge, along with wind, contribute to risk of power outages in hurricanes. By conducting a longitudinal study of outages at the zip code level, we were able to gain insight into the causal drivers of power outages during hurricanes. Our analysis showed that the correlation of storm characteristics with power outages and the importance of the covariates can vary geographically. In Louisiana, during Hurricane Isaac, rainfall and previous outages were the most important covariates in the north, while both rainfall and wind were important in the southeast. Rainfall, wind, and previous outages were all relatively important in the southwest. With the exception of a few zip codes, storm surge was generally not an important variable in predicting power outages, reinforcing the findings of Guikema et al. (2014) which also found that hurricane storm surge was not a particularly important variable in predicting power outages from hurricanes. The geographical variation of the correlation between storm characteristics and power outages is likely due to physical characteristics of the location and of the storm. In areas where the highest wind speeds are experienced, wind is likely to be the most important covariate. Elsewhere, the importance of covariates differs geographically.

While a Random Forest model proved to offer good out of sample predictive accuracy for this data set, a Quantile Regression Forest provided additional information about the uncertainty in and accuracy of the estimates. We found that modeling only hours with delta outages greater than one resulted in improved predictive accuracy. The low-outage periods proved to be difficult to model accurately, as one would expect. Hours with small but positive increases in outage counts at the zip code level are more likely associated with random events than the types of larger-scale system damage that cause higher magnitude outages.

Based on previously published modeling efforts that focused on wind-related covariates to predict power outages, one might expect that wind speed would be the most significant covariate in our model, particularly in areas that experienced high wind speeds. Wind speed was of high importance in areas with high wind speeds, but cumulative precipitation was of moderate to high importance in more parts of the state, and was also important in the areas that experienced high winds. Storm surge was of limited importance in most areas, including those that experienced storm surge. These results point to the conclusion that the use of only wind related variables in power outage forecasting models may result in a less accurate model than one that includes additional variables such as precipitation and perhaps surge inundation, especially in areas outside of the highest wind areas. Storm characteristics and their importance vary from storm to storm, and while many outages may be driven by wind, power outage modelers should include other covariates, particularly precipitation, to improve their model's robustness to differing storm conditions.

In addition to storm characteristics differing from storm to storm, our findings indicate that correlation of storm characteristics with power outages can vary geographically. It is unclear if this variation is due to characteristics of the storm, or other geographic considerations such as topography, power system characteristics, vegetation, and soil types (Quiring et al. 2011). Completing this type of analysis over multiple storms might clarify the reasons for this variation. Analysis of multiple hurricanes would also help assess the robustness of this analysis, and would be useful in informing the development of a power outage model for a state or region. This type of longitudinal analysis could result in a better understanding of the drivers of power outages and in better predictive models.

Chapter 3 Basin Characteristics as Risk Factors for Unexpected Flood Frequency

3.1 Introduction

Flood frequency analysis is a commonly used tool for quantifying flood risk. Flood frequency analysis involves statistical analysis of stream gage records in order to estimate peak flow rates for specified recurrence intervals. While flood frequency analysis is useful and widely used, it is based on limited data sets and uncertainty in the methods is considerable. Additional statistical analysis may serve to better evaluate flood risk and identify conditions for which standard flood frequency analysis may misestimate flood risk. This project involves statistical analysis of basin characteristics and flood frequency data to better understand the conditions under which a widely used flood frequency estimation method provides estimates with a low likelihood of observed record. The focus of this research is 100-year flood events in the Mid-Atlantic region.

One of the first steps typically completed in assessing and managing flood risk is flood frequency analysis. Flood frequency analysis is often followed by hydraulic modeling to estimate flood elevations at specific locations. These estimates of flood elevations can be used to generate floodplain maps. Floodplain maps are used by communities as tools to regulate development in and around floodplains and are developed by FEMA for use in establishing flood insurance rates.

CHAPTER 3 BASIN CHARACTERISTICS AS RISK FACTORS FOR UNEXPECTED FLOOD FREQUENCY

Many flood risk management decisions are based on flood frequency analysis and floodplain maps generated using flood frequency analysis.

Flood frequency analysis is the foundation of much flood risk management, but is often done within a very narrow framework by practicing engineers and hydrologists. This narrow decision-making process carries considerable uncertainty with it, as the analysis is primarily based on available stream gage data and a single flood frequency distribution in practice (Merz and Thieken 2005). The 100-year event was meant to be a preliminary approach, but has become a de facto standard for flood risk management in the United States (Galloway 2011). Quite often the 100-year flood (the flow rate with a 1% probability of occurring or being exceeded in a given year) is used for design, analysis, and decision-making with little regard for how uncertainty factors into this figure (Christian et al. 2013). Research is underway to improve standard flood frequency analysis methods (Stedinger 2008). However, flood frequency results in the form of Federal Emergency Management Agency (FEMA) flood insurance rate maps and studies are in wide use, and even with improved flood frequency analysis methods, uncertainty will still be considerable.

Some common issues with flood frequency analysis are the lack of a physical basis for determining the underlying flood frequency distribution, and the need to look at flood risk for return periods longer than the period of stream gage record (Lettenmaier et al. 1987). Flood frequency results at stream gages vary, and a single type of distribution for flood frequency may not work equally well at different gage locations (Benson 1962A). Villarini and Smith (2010) noted that spatial heterogeneity was apparent in flood peaks at stream gages in the Eastern U.S. and should be addressed. Villarini et al. (2011) observed a heavier-tailed flood frequency distribution in the Eastern U.S. than in the Midwest, and identified relationships between watershed characteristics and distribution parameters. Some gages experience more 100-year events than would be expected based on flood frequency analysis given the period of record, while others experience less. Additionally, 100-year flows may significantly increase in some regions of the U.S. due to climate change and population growth (Kollat et al. 2012). From a risk analysis perspective, it would be useful to have some estimate of which gages may experience records that standard flood frequency analysis results suggest would be unlikely. The purpose of this study is to use statistical learning methods to identify watershed characteristics that are associated with conditions in which observed records would be judged to be unlikely based on Bulletin 17B results. That is, we seek to identify watershed and gage record characteristics that are associated with low probability records.

3.2 Background

There are various types of flood frequency analysis, and widely used methods include statistical analysis of local flood records, statistical analysis of regional flood records, and rainfall-runoff modeling (Merz and Blöschl 2008). The flood frequency analysis method used in this study is the Bulletin 17B method, developed by the Interagency Advisory Committee on Water Data (1982). This method was selected due to its wide usage and acceptance in the U.S., including regulatory requirements to use the method for certain applications, such as FEMA flood insurance rate mapping. The Bulletin 17B method is an evolution of previous methods developed by the U.S. Water Resources Council and was developed in an effort to provide an accurate and standard method to estimate flood frequency based on stream gage data. Bulletin 17B estimates are based primarily on stream gage records for the stream being studied and use the method-of-moments approach with a log-Pearson Type III distribution to determine the statistical parameters for a given gage station. Bulletin 17B includes methods to incorporate the systematic record, as well as historic data, data from other watersheds, and flood estimates based on precipitation records (IACWD 1982). The method is reasonable and performs well compared to other potential methods (Stedinger 2008).

An update of 17B is likely to be released soon, and will incorporate proposed improvements such as the use of historical and interval data, regional skew computation and precision, and confidence intervals. Generally, it is still unclear what the contribution of nonstationarity is to uncertainty and whether estimates would be improved by including it, and difficulties in resolving the skew may still remain (Stedinger and Griffis 2011, Ouarda and El-Adlouni 2011). Some other suggested approaches to improve the accuracy of flood frequency analysis include more substantial use of historic or paleo flood data (Kirby and Moss 1987). However, historic data are often limited, and there is no certainty that historic data can be found or will improve flood frequency estimates (Payrastre et al. 2011). “A simple model with well-understood flaws may be preferable to a sophisticated model whose correspondence to reality is uncertain” (Lins and Cohn 2011). Because these methods add complexity, it would be useful to have an idea of when they might be necessary due to inaccuracy in the standard method for a given gage.

Studies have been completed to explain how flood magnitudes vary based on physical and climatic characteristics of a basin. A study by Benson (1962B) found that drainage area, main channel slope, and surface area of lakes and ponds were important variables. Watershed characteristics have also been widely used in developing regional regression equations and in estimating flow rates at ungaged basins (Pandey and Nguyen 1999, Lettenmaier et al. 1987, Wiltshire 1985). Statistical characteristics of gage records have also been used in the development of regional models (Burn 1988, Lettenmaier et al. 1987). A study by Kidson and Richards (2005) suggests that it is impossible to determine which flood frequency analysis tool is best for a given basin and that a multi-disciplinary approach employing physical modeling supplemented with regional, historic, and paleoflood information may be best. Studies correlating Bulletin 17B performance with watershed or gage record characteristics seem to be lacking, but one study found that Bulletin 17B had poor performance for basins with negative skew values (Wallis and Wood 1985).

Even with proposed improvements to flood frequency analysis methods, uncertainty will still be considerable, and some stream gages will experience low probability outcomes (e.g., three 100-year events in 50 years of record where a 100-year event is estimated by Bulletin 17B methods). A low probability outcome could be considered an indication that the flood frequency analysis method is less accurate for a particular basin. It could be a signal that more uncertainty exists at a gage location, or that flood risk is either greater or smaller in and around that 100-year floodplain than Bulletin 17B suggests. Conversely, it could be the result of random meteorological events. Given the extensive use of the flood frequency results for flood risk management, it would be useful to understand which gages have low probability outcomes and to identify watershed and stream gage record characteristics that are associated with lower probability of outcome. This would allow risk managers to identify study locations where they might want to consider more complex flood frequency and risk analysis methods versus those where they might be more comfortable using standard flood frequency results. This study applies statistical learning methods to this problem to generate a model of probability of outcome versus watershed characteristics. The use of probability of outcome as a measure of flood frequency model accuracy appears to be a novel approach.

3.3 Methods and Data

3.3.1 Data

Stream gage data for this project were obtained from the United States Geological Survey National Water Inventory System (NWIS) website (U.S. Geological Survey National Water Information System. Accessed November 10, 2014, http://nwis.waterdata.gov/nwis.). Annual peak streamflow data were retrieved for the stream gages with at least 40 years of record in the states of Delaware, Maryland, Pennsylvania, West Virginia, Virginia, and North Carolina. Only stream gages with 40 years or more of non-regulated flow were included in the analysis, resulting in a total of 417 gages. The record lengths for the gages used in this analysis ranged from 40 to 119 years, with an average record length of 67 years.

Flood frequency analysis was performed for each stream gage using the PeakFQ software, which implements the Bulletin 17B methods. Streamflow qualification codes were evaluated and peaks were disqualified based on the specifications in the PeakFQ manual (Flynn et al. 2006). This included peaks affected by dam failure and known effects of regulation, urbanization, or other watershed change. Adjustments were made for low outliers, while high outliers were retained without adjustment. Weighted skew values based on the station skew and generalized regional skew were used. The generalized skew values for Delaware were obtained from a U.S. Geological Survey (USGS) report (Ries and Dillow 2006). The generalized skew values for Maryland were obtained from the Maryland Hydrology Panel report (2010). For Virginia, a study of generalized skew estimates was not available, so the generalized skew values were based on the generalized skew coefficients map in Bulletin 17B, with values generated in PeakFQ based on station location (Austin et al. 2011). For West Virginia, skew values were obtained from a USGS report (Wiley and Atkins 2010). For Pennsylvania, skew values were obtained from a US Army Corps of Engineers (USACE) report on the Delaware River Basin (Goldman et al. 2009), and from a USACE statewide report (Roland and Stuckey 2008). For North Carolina, skew values were obtained from a USGS report (Weaver et al. 2009). When historic data were available in the gage record, a historic adjustment was performed. No further adjustments (e.g. two-station comparisons) were included in order to maintain consistency and the simplest implementation of the Bulletin 17B methods.

Once the 100-year streamflow was estimated for each gage, this value was compared to the annual peak streamflow record for each gage to determine the actual number of years in the period of record in which the peak annual streamflow met or exceeded the estimated 100-year streamflow rate. This actual number of years for each gage that include a 100-year event is termed the “outcome” for purposes of this study. A conceptual probability of outcome for each gage was calculated using the binomial equation presented as equation 1. In this equation, n is the number of years of record for the gage, k is the number of years in which the peak annual streamflow rate met or exceeded the 100-year flow rate, and p is 0.01, which is the probability of experiencing at least one 100-year streamflow event in any year. In this calculation, the likelihood of a 100-year flood event occurring in any given year remains constant over the entire period of record and is independent of events occurring in other years. For example, a stream gage that had one 100-year event in 50 years of record would have a probability of 0.31.

$$P(X=k)=\left[\frac{n!}{k!(n-k)!}\right]p^k(1-p)^{(n-k)} \qquad [1]$$

Probability of outcome was plotted and evaluated geospatially to identify any potential spatial trends. A histogram of probability of outcome was also generated. In order to determine whether the distribution of the probability of outcome values for the set of gages as a whole were as should be expected given the number of stream gages and the length of record for each of the gages, a synthetic record analysis was completed. For each stream gage, a synthetic record of number of 100-year events was generated using the actual number of years of record for each gage and a probability 0.01 of a 100-year event occurring in a given year. The probability of this record was then calculated, yielding one replication for that gage. 100,000 replications were performed for each gage and the set of synthetic probabilities for all gages was used to generate a synthetic distribution of probability of record. The density of this synthetic distribution was plotted along with the density of the probabilities based on the actual data set to evaluate how the actual probabilities compare to theoretical expected probabilities, given the length of record at each of the gages.

We see from Figure 3.1 that there are less low-probability gages and more high-probability gages in the dataset than would be expected. However the underrepresentation of low-probability gages does *not* mean that these are not problematic. It is these gages where Bulletin 17B estimates lead to the existing record being judged to be unlikely. This leads to flood risk that is either higher or lower than Bulletin 17B would suggest. Understanding which watershed and stream gage characteristics are associated with these low-probability estimates is the major goal of this work.

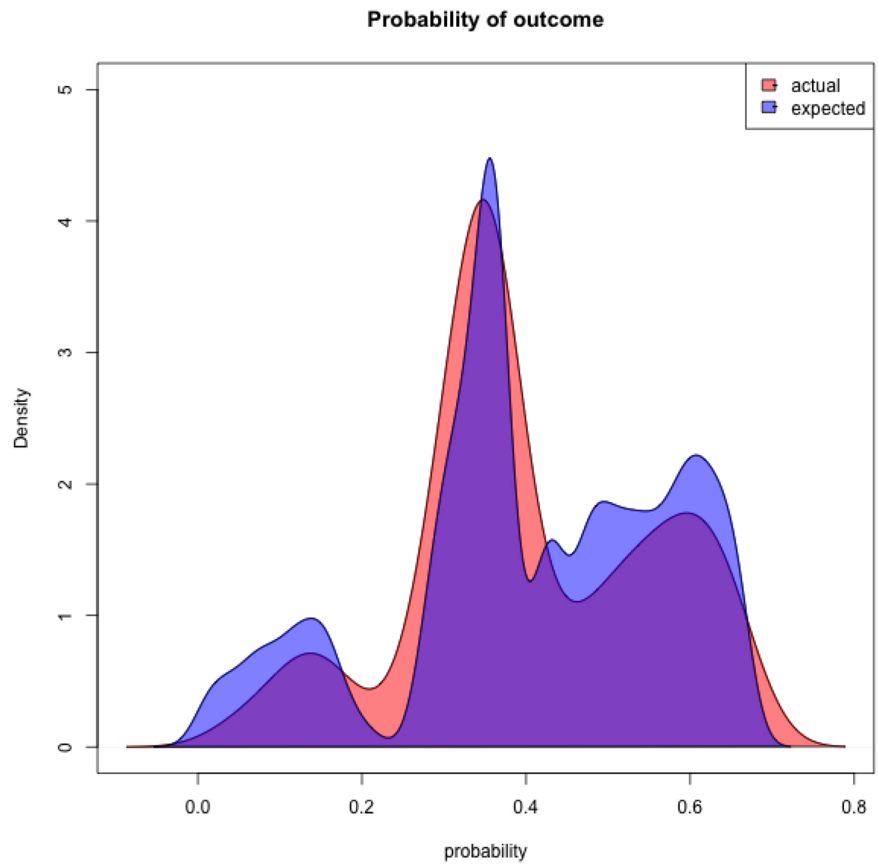

Figure 3.1: Density of probability of outcome. Red represents density of probability of outcome for the 417 studied stream gages. Blue represents density of probability of outcome from the synthetic probability analysis.

Watershed data were obtained from the USGS GAGES II (Geospatial Attributes of Gages for Evaluating Streamflow) data set (U.S. Geological Survey GAGES-II: Geospatial Attributes of Gages for Evaluating Streamflow digital spatial dataset. Accessed November 19, 2014. http://water.usgs.gov/lookup/getspatial?gagesII_Sept2011). This data set, which was published in 2011, contains basin characteristic data for USGS stream gages. Covariates were chosen to reflect commonly used watershed characteristics that could conceivably be related to either the accuracy of the flood frequency analysis method, the runoff generating mechanisms for the watershed, or the meteorological conditions at the watershed location. The covariates fall into the following categories: Basin Identification, Basin Classification, Basin Morphology, Climate, Geology, Hydrology, Hydrologic Modifications, Landscape Patterns, Land use, Population and Infrastructure, Soil, and Topography. The full list of the 61 covariates used in the analysis is included in Appendix A.

3.3.2 Statistical Modeling

Statistical analysis was performed using the R software (R Development Core Team 2008). Initially, several models appropriate for the response variable, probability of outcome, constrained to the 0 to1 interval were selected and run, including beta regression, Classification and Regression Trees (CART), and Random Forest. Based on the results of this initial analysis, Random Forest was chosen as the best model and was used for the remainder of the analysis.

Random Forest is a non-parametric ensemble decision tree method. In the method, a large number of regression trees are developed, with each tree based on a bootstrapped sample of the data set. The prediction is averaged from the set of trees. Random Forest models are good for data sets with non-linear relationships, outliers, and noise (Hastie et al. 2001).

Several Random Forest models were generated with different selections of covariates: 1) all watershed covariates included, 2) all watershed covariates included plus the mean, standard deviation, and skew of the stream gage record, 3) subset of watershed covariates selected to reduce physical redundancy, and 4) subset of watershed covariates selected to reduce physical redundancy plus the mean, standard deviation, and skew of the stream gage record. Holdout analysis was run with 50 repeated, random holdouts with a randomly selected 20% of the data held out each time, and the predictive accuracy of the models was compared to each other and to a mean-only model where predictions were made using only the mean probability for all gages. A Random Forest model was selected as the best model because its predictions had the lowest mean squared error (MSE) and mean absolute error (MAE). A subsequent analysis was run on the selected model using the caret package in R to determine whether a model with a reduced number of covariates would result in improved predictive accuracy.

Two key types of Random Forest output are used for analyzing the model results. Variable importance is calculated as the percent increase in MSE resulting from permuting each covariate and recording the out-of-bag prediction error (James et al. 2013). This is a measure of the contribution of each variable to the out of sample predictive accuracy of the model. Partial dependence plots show the marginal influence of a covariate on the response variable after integrating out the other covariates (James et al. 2013).

3.3.3 Clustering

To further explore the relationship between key covariates and the probability of outcome, k-means clustering was performed. K-means clustering is a method to partition a data set into a specified number of non-overlapping clusters based on data values (James et al. 2013). The purpose of this analysis was to determine whether certain ranges of covariate values might be associated with low probability outcomes. Based on preliminary evaluation of the most functional number of clusters for purposes of this analysis, four clusters was chosen for the k-means analysis, and the stream gages were separated into four clusters based solely on probability of outcome. Empirical CDF (ECDF) plots were generated for each cluster, for each of the six most important covariates from the Random Forest model, and are presented alongside the partial dependence plots for each covariate.

3.3.4 Bootstrapped Data Analysis

In order to partially address the limitations of our study pertaining to the variation in years of record for stream gages, we generated ten bootstrapped samples of 40 years of record for each gage. Because each bootstrap sample had exactly 40 randomly drawn years of record we eliminated the effect of differing stream gage record lengths. This yielded ten separate bootstrapped data sets. Results from the bootstrapped analysis were compared to the results of the analysis of the full data set to determine if the same variables had high importance, and how the variable importance differed amongst the data sets.

3.4 Results and Discussion

3.4.1 Probability of Outcome

In order to understand how probability of outcome varied geographically, a map of the study area and the probability of outcome for each stream gage was generated. This map is included as Figure 3.2. The red dots on the map represent the stream gages with the lowest probability of outcome values. Because of the nature of precipitation and flooding events, some grouping of low probability stream gages was expected. However, visual analysis of Figure 3.2 fails to show any spatial grouping of similar probability gages. This indicates that low probability outcomes are not confined to a certain geographic portion of the study area and are not generally grouped geospatially.

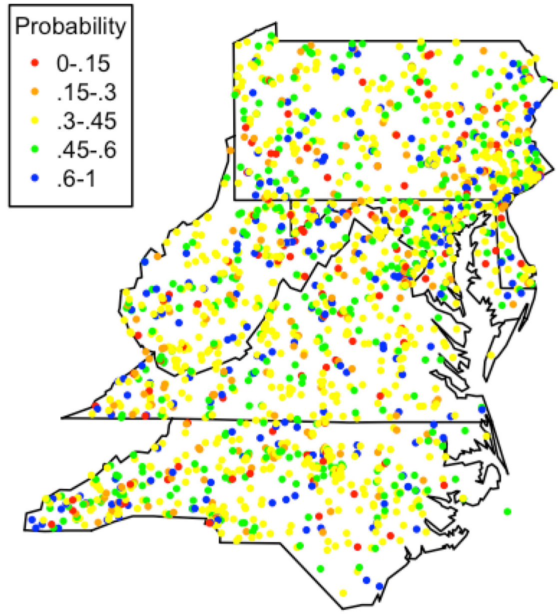

Figure 3.2: Plot of probability of outcome for stream gages analyzed

3.4.2 Statistical Model and Clustering Analysis

In order to evaluate the accuracy of the Random Forest model, and to choose the model with the best predictive accuracy, holdout testing was performed. The results of the holdout testing are provided in Table 3.1. All models compared provided an improvement in fit over the mean-only model. Model 4 included a subset of 33 covariates selected to reduce physical redundancy, plus the mean, standard deviation, and skew of the gage record. In generating this model, covariates representing similar physical characteristics were removed. For instance, the average basin temperature covariate was retained, while the maximum basin temperature covariate was removed. This model had the lowest average mean absolute error (MAE) and average mean squared error (MSE) across the holdout tests and was selected for further analysis. The differences between model 4 and all models except model 2 were statistically significant at a 0.05 overall level

(Bonferroni-corrected). Model 2 and model 4 yield similar predictive accuracy, but model 4 uses less covariates. We used model 4 for further analysis for reasons of parsimony.

Table 3.1: Comparison of model predictive accuracy based on Average MAE and MSE

Model	**Covariates included**	**Avg. MAE (std.dev)**	**Avg. MSE (std.dev.)**
1	All watershed covariates	0.118 (0.0082)	0.022 (0.0026)
2	All watershed covariates plus stream gage mean, standard deviation, and skew	0.110 (0.0081)	0.019 (0.0023)
3	Subset of watershed covariates selected to reduce physical redundancy	0.118 (0.0082)	0.022 (0.0025)
4	Subset of watershed covariates selected to reduce physical redundancy plus stream gage mean, standard deviation, and skew	0.110 (0.0082)	0.019 (0.0023)
Mean Only	Mean of probability for all stream gages in the training set used as prediction for the holdout set	0.123 (0.0079)	0.023 (0.0026)

To determine whether model accuracy could be improved by using a subset of the most important covariates from the selected model, recursive feature elimination was performed using the CARET (Classification and Regression Training) package in R with 200 bootstrap samples. In recursive feature elimination, backwards selection of covariates is performed based on importance ranking. Less important covariates are sequentially removed to identify the subset of predictors that provides the most accurate model. The output indicated that a reduction in covariates from the selected model would not result in a more accurate model. Thus, the selected model was used for the remainder of the analysis.

Figure 3.3 shows the top six most important covariates, based on the Random Forest variable importance calculated as the percent increase in MSE. As shown in Figure 4, stream gage skew was the most important covariate, followed by drainage area, mean flow (mean peak annual log flow rate), road-stream intersections, percent forested area in watershed, and percent developed area in watershed.

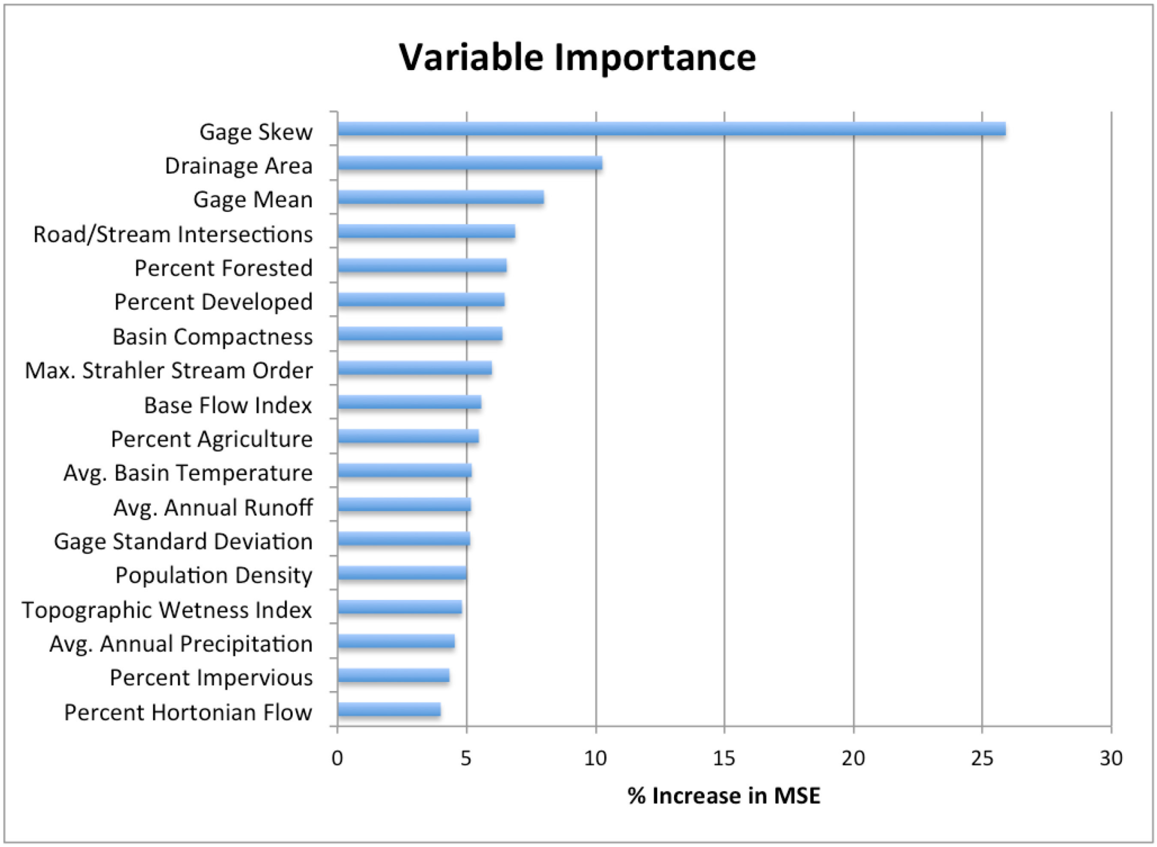

Figure 3.3: Random Forest Variable Importance

In order to further analyze the influence of the covariates, partial dependence plots and empirical cumulative distribution function (CDF) plots were generated for the each of the six covariates. The partial dependence plots show the marginal influence of the covariate on the response variable. In each of the partial dependence plots, the influence of the covariate changes with the covariate values.

We partitioned the response variable into four groups using k-means clustering and then plotted the ECDFs for each of the four groups in order to better understand how different or similar the covariates are across different ranges of the response variable. The objective was to identify differences in covariate values that are associated with low probability outcomes. Cluster 1 includes 216 stations and is centered at probability = 0.34, with a probability range of 0.27 to 0.42. Cluster 2 includes 74 stations, and is centered at probability = 0.50, with a range of 0.43 to 0.56. Cluster 3 includes 44 stations, and is centered at probability = 0.13, with a range of 0.03 to 0.22. Cluster 4 includes 83 stations, and is centered at probability = 0.62, with a range of 0.56 to 0.67. The partial dependence and ECDF plots for each of the six covariates are shown in Figures 3.4 through 3.9. The results of these ECDFs and the partial dependence plots are discussed for each of the top six covariates.

Gage Skew – The skew of the stream gage record represents the asymmetry of the values about the mean. Gage skew is included as an input in the 17B flood frequency analysis method. The partial dependence plot in Figure 3.4 shows that predicted probability tends to decrease with increasing skew. In the ECDF plot, the stream gages in the lowest probability cluster (cluster 3) tend to have higher skew values than the stream gages in the other clusters. Skew is used in the Bulletin 17B method to fit the stream gage record to the log Pearson type III distribution. A higher skew value would indicate that the shape of the distribution is wider on the right side than on the left side, that is, it is right-skewed. This indicates that gages with a greater number streamflow events at the high end of the distribution are more likely to have low probability outcomes, which is likely due to a poor fit with the thin-tailed log Pearson type III distribution.

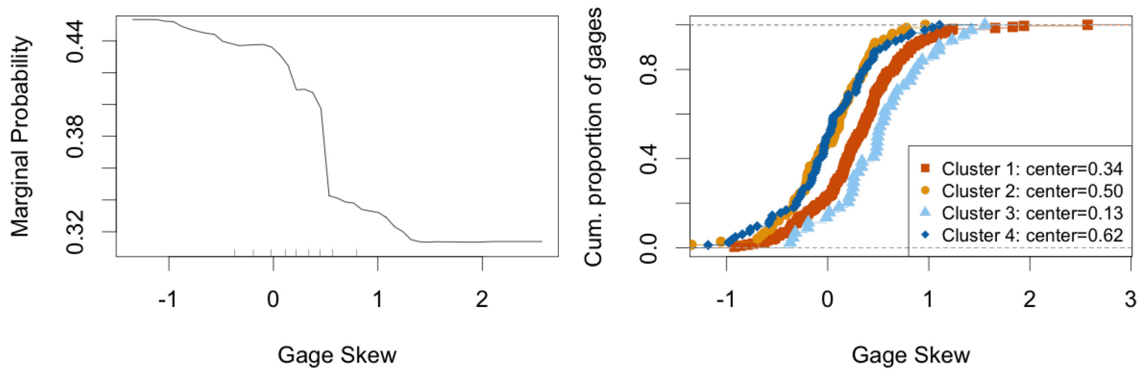

Figure 3.4: Partial dependence and ECDF plots for Gage Skew

Drainage Area – Drainage area is defined as the watershed area that drains to the stream gage location, and in our study has units of square kilometers. The partial dependence plot in Figure 3.5 indicates that lower probability predictions generally tend to have higher drainage areas. The partial dependence plot is flat for very high values of drainage area where there are very few data points. The ECDF plot shows that stream gages in the lowest probability cluster generally tend to have larger drainage areas. This may be due to greater spatial variation in storm events and resulting runoff generation in larger basins than in smaller basins where precipitation events are more likely to impact the entire basin concurrently and land use may be more consistent.

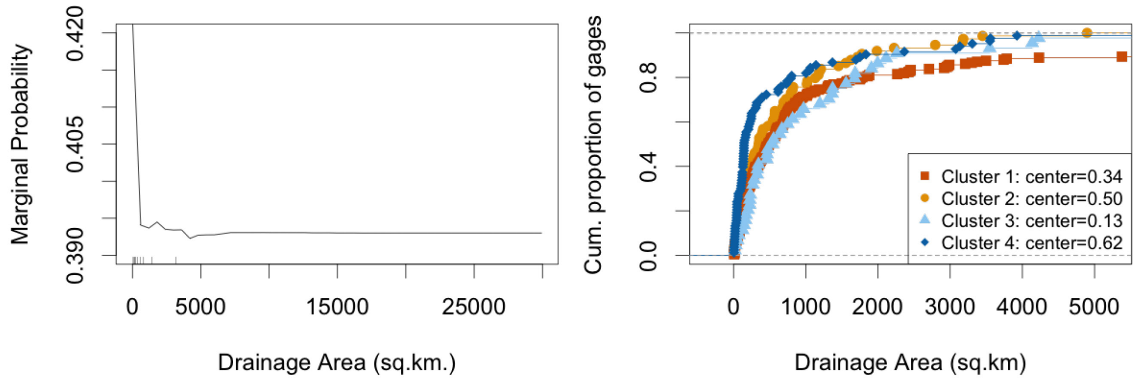

Figure 3.5: Partial Dependence and ECDF plots for Drainage Area

Mean Flow – The mean of the log of the stream gage peak annual flow rate serves as an indicator of the magnitude of the peak flow rates at the gage. The partial dependence plot in Figure 3.6 shows that the lowest probability predictions tend to have higher mean flow values, generally above 3.5. The ECDF plot also indicates that the lowest probability cluster tends to have slightly higher mean flow values than the other clusters. This result is consistent with the Drainage Area result. While other basin characteristics influence flow generation, basins with higher mean flow would generally tend to come from basins with larger drainage areas.

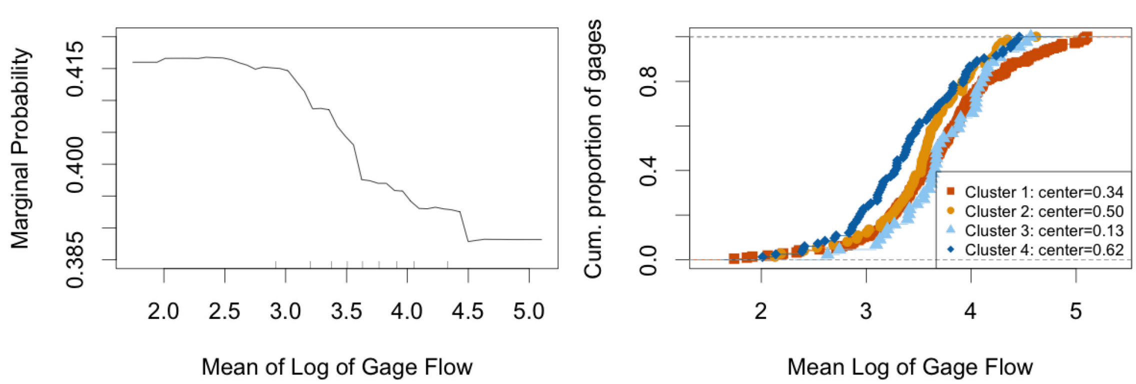

Figure 3.6: Partial Dependence and ECDF plots for Gage Flow

Road-Stream Intersections – This covariate is a count of the number of road and stream intersections per kilometer of stream length. A higher value could indicate a more developed watershed or a more urbanized stream channel. The partial dependence plot in Figure 3.7 indicates that lower probability predictions tend to have values of road-stream intersections in the range of 0.4 to 0.7. The ECDF plot shows that the majority of the data points for the lowest probability cluster fall within this range, and shows only very slight differences between the values for the different clusters. Low probability gages tend to have values of road-stream intersections that lie in the low to mid-range of observed values. The reasons for this are unclear, but warrant follow up investigation.

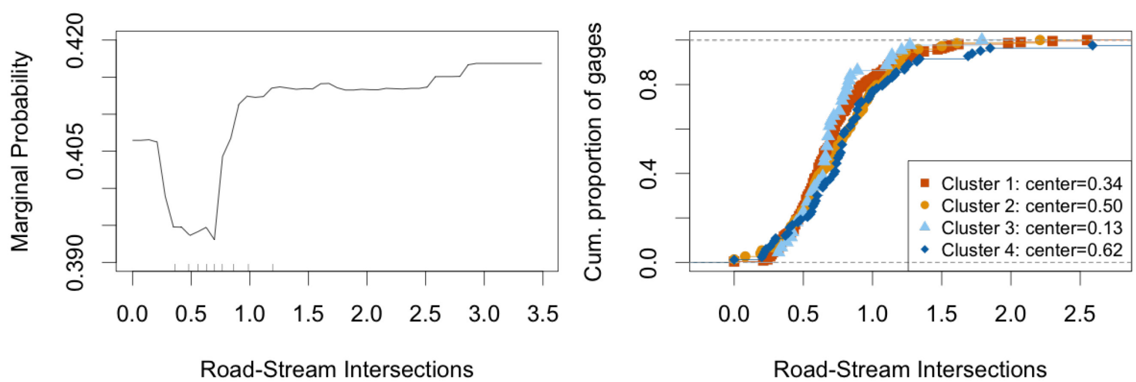

Figure 3.7: Partial Dependence and ECDF plots for Road-Stream Intersections

Percent Forested – This covariate describes the percentage of the watershed with forested land cover, measured in 2006. The partial dependence plot shown in Figure 3.8 indicates that above about 20% forested, the percent forest tends to increase with predicted probability. The ECDF plot indicates that the lowest probability cluster includes a number of gages in the 20 to 30% forested range, but above that the lowest probability cluster is similar to the other clusters. For basins with a relatively low percentage of forested land, this covariate is an important predictor for low probability outcomes. Basins with low percentages of forested land may tend to be more developed or urbanized and generate more runoff per unit of precipitation input than more forested or natural basins.

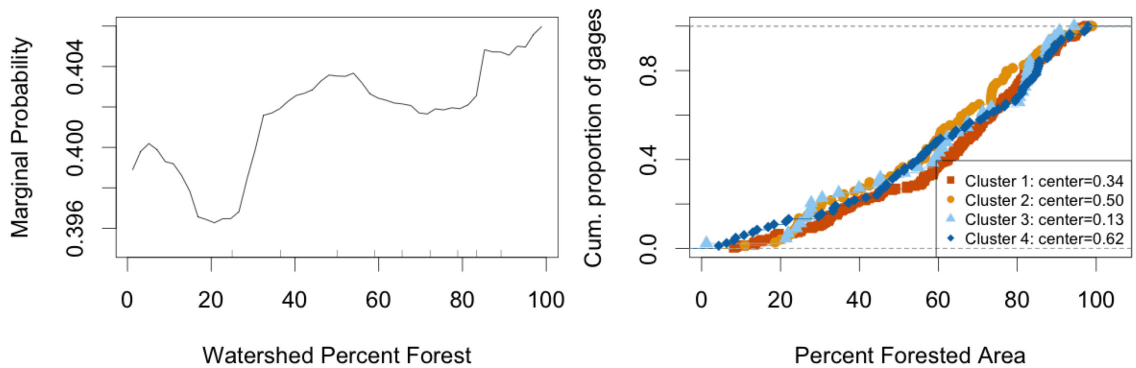

Figure 3.8: Partial Dependence and ECDF plots for Percent Forested Area

Percent Developed – Percent developed describes the percentage of developed area in the watershed, as measured in 2006. The partial dependence and ECDF plots in Figure 3.9 shows that the majority of the values for this covariate are in the 5 to 25 percent developed range. The lowest probability predictions tend to have values in the 5 to 10% developed range. This result seems somewhat counterintuitive given the result for percent forested, wherein basins with low percent forest tended to have lower probabilities. Generally, we would expect basins with low percent forest to have higher percent developed area. It is possible that basins with very low percent developed have streamflow distributions that differ from basins with more typical development percentages and fit the log Pearson Type III distribution poorly compared to those basins. This point warrants further follow-up research.

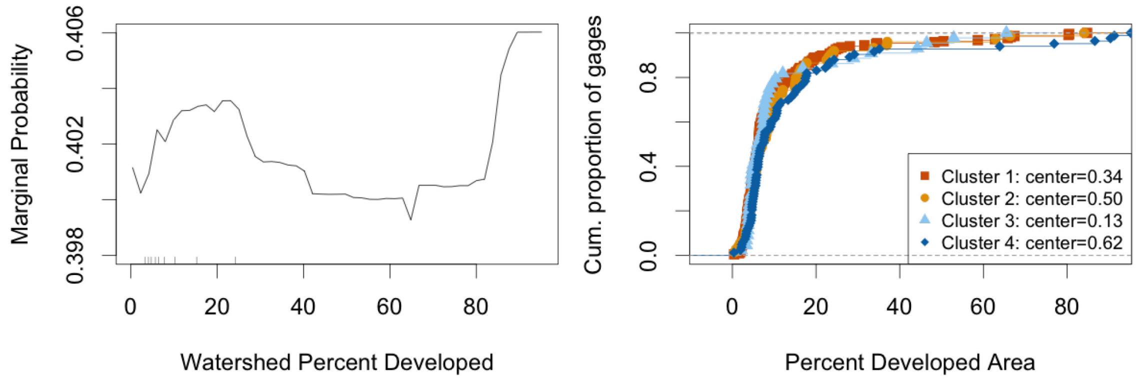

Figure 3.9: Partial Dependence and ECDF Plots for Percent Developed Area

In reviewing the partial dependence plots, the marginal influence of the gage skew covariate spans a range of 0.14. The marginal influence for each the other covariates is less, spanning ranges of about 0.025 for drainage area and gage mean, the next most important covariates, to 0.004 for percent developed, the least important of the six covariates. While the marginal influence of these covariates is somewhat small, summing these influences could result in significant influence on the response variable. Higher skew values, larger drainage areas, higher mean peak annual flow, moderate road-stream intersections, lower percent forested area, and lower percent developed area are watershed characteristics associated with lower probability outcomes. The ECDF plots corroborate the findings of the partial dependence plots. This points to the conclusion that the accuracy of standard flood frequency analysis results may not be equivalent for all watersheds.

3.4.3 Bootstrapped Data Analysis

Using the covariates included in Random Forest model 4, a Random Forest model was created for each of the ten bootstrapped samples. The purpose of this analysis was to determine whether the same covariates had high variable importance in randomly selected sets of equal record length. Because each bootstrapped gage data set contained exactly 40 years of record, only a limited number of discrete probability of outcome values were possible. Therefore, the response variable was treated as categorical for this analysis. In each bootstrapped model, gage skew was the most important covariate. The importance of the other covariates varied. In addition to the six covariates of higher importance in our original model, covariates with high importance in the models for some of the bootstrapped data sets included fragmentation index, standard deviation of gage record, population density, elevation at gage location, and average annual runoff.

Additionally, the range of variable importance for each covariate in the bootstrapped models was evaluated, and boxplots of the relative importance of the covariates is displayed on Figure 3.10. Because the magnitude of variable importance values differs for each Random Forest run, the variable importance is plotted as a percent of total variable importance, so that the different runs can be compared (Tonn et al. 2016). Review of Figure 3.10 indicates that the variable importance for gage skew, percent forest, and percent developed in the original model is near the median percent importance for these covariates in the bootstrapped analysis. Variable importance for drainage area and mean flow for the original model are at the upper end of the range of importance for these covariates in the bootstrapped analysis. The road-stream intersections covariate had much lower importance in the bootstrapped analysis than in the original model. This indicates that the length of gage record and the specific realization of the gage record do influence which covariates are important. However, with the exception of road-stream intersections, the bootstrapped analysis reinforced the finding of the importance of the top six covariates from the original analysis.

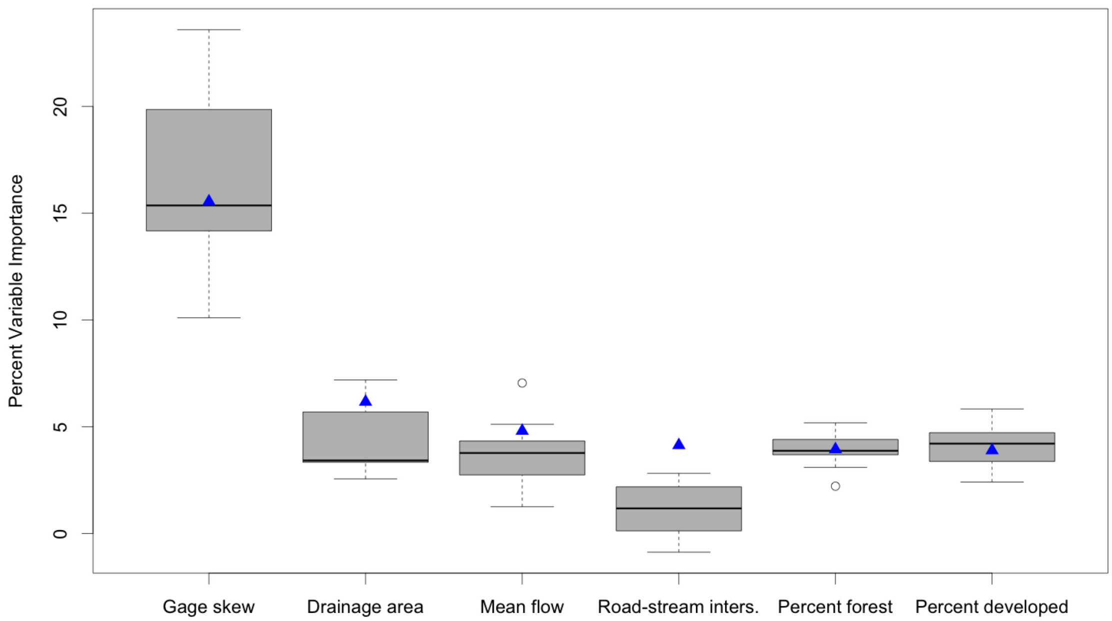

Figure 3.10: Percent variable importance for bootstrapped data analysis (box plots) and percent variable importance from original model (triangular points)

3.5 Conclusions

The synthetic streamflow record analysis indicates that for the Mid-Atlantic region, the Bulletin 17B method is producing fewer low probability outcomes than should theoretically be expected. However, given the extensive use of flood frequency analysis results for flood risk management, it would be useful to be able to identify stream gages that are likely to have low probability outcomes when judged relative to a Bulletin 17B analysis and to identify watershed characteristics that may be correlated with probability of outcome. This would allow risk managers to identify stream gages where they might want to consider more advanced flood frequency and flood risk analysis methods versus those where they might be more comfortable using basic flood frequency results. This study is an effort to apply statistical learning methods to this problem to generate a model of probability of outcome versus basin characteristics.

Choosing a response variable for this analysis was challenging, and probability of outcome was selected as the most feasible option. Using probability of outcome as a response variable allows for stream gages with differing record lengths to be analyzed as a set. It provides a value for analysis that gives an indication of the likelihood or expectedness of the peak annual streamflow record at a gage, in light of the Bulletin 17B 100-year flow estimate. However, there are limitations associated with the use of this response variable. The definition of the response variable is somewhat convoluted, and the value does not give an indication of whether a low or high probability value is due to an excess or a deficit of 100-year events. Other potential response variables, such as ratio of actual to expected years with 100-year events, or deviation from the expected number of years with 100-year events, have limitations associated with disparate periods of record.

Random Forest models with different covariate selections were compared. Variable importance and partial dependence plots were generated and analyzed to interpret model output. Clustered data analysis was performed to further analyze the relationship between the covariates and probability of outcome. Covariates that are associated with lower probability of outcome in the Mid-Atlantic region included higher gage skew, larger drainage area, higher mean peak annual flow rate, moderate road-stream intersections, and lower percent forested and percent developed. The clustering analysis reinforced the findings of the Random Forest model, and showed that cumulatively, gages with a low probability of outcome had values for several covariates that were generally higher or lower than most other gages. In both the original analysis and an analysis of ten bootstrapped data sets, gage skew was the most important covariate. In evaluating the ECDF plot for gage skew, there was clear separation in skew values for the lowest probability cluster as compared to the other clusters. Gages with higher skew values are more likely to have low probability outcomes. This makes sense given that these gages have distributions that are right-skewed and given the significance of the skew value in the Bulletin 17B calculations. While the skew values are weighted with regional skew values in the Bulletin 17B calculations, higher gage skew values are clearly correlated with lower probability outcomes.

The results of this study identify the covariates that are most important in modeling probability of outcome at stream gages in the Mid-Atlantic region. The key finding is that certain watershed characteristics are correlated with probability of outcome, indicating that the results of standard flood frequency analysis may not be equivalent across differing watersheds. Analysts may want to consider enhanced flood frequency methods for watersheds with these characteristics. These results can be used in evaluating floodplain maps generated using the Bulletin 17B methods, such as FEMA flood insurance rate maps. Watershed characteristics could be compared to those found to be important in this study to determine if a watershed area is more likely to experience an unexpected outcome (i.e. the map is less reliable).

While our model provided an improvement in predictive accuracy over other potential Random Forest models as well as a mean-only model, clearly the model accuracy is limited. Flood frequency is highly dependent on random weather events and other meteorological conditions that could not be captured by this study. This study was limited to stream gages in the Mid-Atlantic region, and the findings may not apply to other regions. The study included only the 100-year return period, and results might differ for other return periods. This study focused on the Bulletin 17B flood frequency method, but the new 17C method could be evaluated in a similar manner.

Chapter 4. An Agent-Based Model of Evolving Community Flood Risk

4.1 Introduction

In the United States, floods cause an average of 140 deaths and $6 billion in damages per year (excluding Hurricane Katrina) (Stedinger 2008). Flooding is the most common natural hazard and the third most damaging globally, behind storms and earthquakes (Wilby and Keenan 2012). Flooding and floodplain management are subjects that have been long-studied. However, flood damage and flood risk continue to increase in the U.S. and abroad (Wilby and Keenan 2012, Kron 2005). Climate change is anticipated to result in changes in frequency, intensity, spatial extent, duration, and timing of extreme weather. This could result in unprecedented extreme weather and climatic events, which would significantly impact flood risk (Field 2012). This research investigates how behavior, policy, climate change, and engineering interventions impact riverine flood risk. The purpose of this research is to inform flood mitigation and adaptation decision-making.

Flood risk is often studied using hydrologic and hydraulic models, and decisions are made based on these models together with benefit-cost calculations and considerations of acceptable risk levels. However, these models involve considerable uncertainty about flood risk, and do not capture impacts of community policies and individual decisions on the evolution of flood risk over time. Individual behavior, including the decision to implement mitigation, to move in or out of flood prone areas, and to purchase insurance, plays a major role in community flood risk.

Community flood risk is managed through regulations, insurance, and mitigation projects. Flood mitigation projects can be implemented on a community or a regional basis and may include soft measures like warning systems and evacuation plans and hard measures like levees and dams. These measures are undertaken to reduce property damage and increase public safety. However, poorly planned or executed flood mitigation projects can have unanticipated consequences, such as reduced ecosystem services, and can even result in increased flooding and reduced public safety (Criss et al. 2001). Furthermore, flood control measures can create more damage by enticing development in marginally protected areas. This creates a cycle of development and structural flood mitigation (Birkland 2003). Consideration of the behavioral aspects of flood risk is crucial to minimizing these negative flood mitigation consequences, particularly when examining the evolution of flood risk over time in a given location.

The purpose of this study is to improve the understanding of the temporal aspects of flood risk through a combined analysis of the behavioral, engineering, and physical aspects of flood risk. Additionally, the study aims to develop a new modeling approach for integrating behavior, policy, flood hazards, and engineering interventions. This research will improve understanding of temporal changes in community flood risk through a combined analysis of the behavioral, engineering, and physical hazard components of flood risk. The hypothesis is that the interaction of policies, individual behavior, and flood mitigation measures can result in unanticipated changes to flood vulnerability that are not captured by standard engineering-based models. An agent-based model (ABM) is used to analyze the influence of flood protection measures, both structural and non-structural, individual behavior, policies, subsidies, and the occurrence of floods and near-miss flood events on community flood risk. The ABM focuses on the following decisions and behaviors: dissemination of flood management information, installation of community flood protection, elevation of household mechanical equipment, and elevation of homes. The approach is place-based, with a case study area in Fargo, North Dakota, but is focused on generalizable insights into the roles of individual and community action and climate in driving the evolution of flood risk.

There are several key questions that this study strives to address:

- How does community flood risk evolve over time in light of stochastic flood outcomes, individual behavior, and community interventions?
- How might community flood risk differ under future climate scenarios?
- Is Agent-Based Modeling a useful tool for simulating evolving flood risk?

Section 4.2 provides background regarding the behavioral aspects of flood risk and agent-based models. Section 4.3 describes the modeling inputs and process. Section 4.4 presents results, Section 4.5 provides a description of the strengths and limitations of Agent-Based Models, and Section 4.6 provides a summary and conclusions.

4.2 Background

4.2.1 Human Behavior and Flood Risk Perception

In reviewing the relevant literature, it is clear that experience and beliefs play a significant role in individual flood mitigation behavior. In a study of perceptions of flood risk on the Red River of the North following the 1997 flood, it was found that a community that has been exposed to a natural hazard cannot be treated as a homogenous group. Responses depend on experience, background, and personal viewpoint (Burn 1999). Siegrist and Gutscher (2008) found that flood experience results in increased perceived risk and preventative behavior. People affected by past floods are more likely to implement structural flood mitigation measures. Those without flood experience envision flood consequences differently than those with experience. Insecurity and uncertainty stay in the minds of those that have flood experience, though they do not always implement mitigation measures due to concerns about cost and effectiveness. A study by Bubeck, et al. (2012) found that people who live in risk-prone areas rarely undertake mitigation measures voluntarily, and this contributes to vulnerability. In addition to experience with floods, they point out several factors that impact the adoption of individual mitigation measures including fear or worry about flooding, knowledge about flood hazards, socioeconomic and geographical factors, deterrent factors (i.e. belief that flood mitigation is a governmental responsibility), and perceived effectiveness of mitigation measures. They find that the adoption of individual flood mitigation measures is less related to an individual's perception of the risk and more related to their perception of mitigation options. Risk perception is unique to the individual and is based on prior flood experience, the public's trust in expert knowledge and safety measures, misunderstanding of probabilities, trust in flood control structures, and the assumption that if the government allows you to live in an area it is safe (Ludy and Kondolf 2012).

More generally, disaster research has shown that level of preparedness is significantly linked to individual experience with disasters (Wenger et al. 1980, Dooley et al. 1992, Lindell and Perry 2000, Tierney et al. 2001, Mileti and O'Brien 1992). In particular, past and future disaster events, especially near-misses, become coupled such that the outcomes of prior events might alter perceptions of information about future events (Dow and Cutter 1998, Dillon and Tinsley 2008, Dillon et al. 2011, Tinsley et al. 2012, Collmann and Cooper 2007, Cooper et al. 2008). One of the critical findings from this work is that there is a high degree of variability across individuals in response to repeated events (Dow and Cutter 1998). This suggests that in modeling behavioral responses to floods and flood protection measures, an approach is needed that can explicitly model a high degree of localized heterogeneity in behavioral responses.

A study by Koks et al. (2015) showed the value of joint assessment of hazard, exposure, and social vulnerability. Embanked areas are often low lying and densely populated, and experience low probability but high impact flooding. The density of the built environment should be considered in the exposure component. Vulnerability characteristics have a strong spatial variation and a heterogeneous risk pattern. Areas with elderly and low income people may need tailored flood risk management. The study recommends including both physical and social vulnerability in risk assessment. Integrated Flood Risk Management includes both flood protection infrastructure plus household mitigation measures (Bubeck et al. 2013).

Perceptions of risk and risk related behaviors may amplify the social, political, and economic impact of disasters well beyond their direct consequences. Social facets of flooding have been historically overlooked in flood management. Furthermore, there are still weaknesses in the understanding of flood risk perceptions and mitigation behavior (Birkholz et al. 2014).

4.2.1.1 Threat and Coping Appraisal

Flood-coping appraisal is an important factor in flood risk management behavior. Coping appraisal is the process people go through to evaluate their ability to avoid a certain risk. Threat appraisal involves perceived vulnerability (probability) and perceived severity (consequences). Coping appraisal involves response efficacy (does a person consider the protective measure to be effective), self-efficacy (does the person feel able to implement the measure), and response cost (financial, time, and emotional cost associated with implementing the measure) (Bubeck et al. 2013). Threat appraisals have a small effect on mitigation behavior, whereas coping appraisals have a bigger influence (Poussin et al. 2014).

High-risk perceptions need to be accompanied by coping appraisal for protective response to occur. Perceived risk is a combination of perceived probability and perceived consequences. Studies do not find significant correlation of perceived probability with flood mitigation behavior. Experiences with flooding in the distant past have only a small influence on risk perception and mitigation later in life. Flood awareness mostly diminishes within seven years after a flood and only catastrophic disasters are remembered long-term. Knowledge is not always a good predictor of mitigation behavior (Bubeck et al. 2012).

4.2.1.2 Flood experience

People without flood experience envision the consequences of a flood differently than those with experience. This is due to the concept of availability, wherein people with no flood experience have trouble envisioning and evaluating the consequences. For groups affected by floods, uncertainty, fear, shock, and helplessness were among the worst aspects of a flood. Those without experience rarely mention these aspects. Affected people are more likely to change behaviors and implement structural measures. Experience with a serious flood results in acquiring new information. People with recent flood experience are less convinced that they are well protected. However, people with flood experience may not mitigate due to doubt about effectiveness and high cost (Siegrist and Gutscher 2008).

Perceived personal risk is related to the intensity and frequency of hazard experience. This can involve hazard experience by family, neighbors, friends, and coworkers. Perceived risk is also impacted by information from public authorities and the news media (Lindell and Hwang 2008). Hazard experience increases the adoption of hazard adjustments. Proximity and intrusiveness of the hazard are also relevant (Lindell and Perry 2012).

An individual's subjective perception of risk influences their protective behavior. Most individuals do not make cost-benefit tradeoffs when deciding whether to purchase insurance. According to Dillon et al. (2011), when probabilities are below a certain threshold, people tend to assume a bad outcome can't happen to them. They weight low-probability events as "no probability" events. Personal experience with disasters significantly influences the demand for insurance. Perceptions of flood risk are strongly influenced by past experience. Experts pay more attention to the probability whereas the general population pays more attention to the consequences, and statistical risk is just one piece of information that people consider along with other types of risk information (Dillon et al. 2011).

4.2.1.3 Near-miss flood events

In general, research shows that rather than serving as warning signs and increasing risk perception, near-miss flood events are often judged as successes. Lower levels of perceived risk encourage people who have experienced near-miss events to make riskier decisions. Near-misses can lead to complacency and can lower perceived risk. People are generally more influenced by what did happen than what might have happened (Dillon and Tinsley 2008).

As noted by Dillon et al. (2011), people mistake good fortune as an indicator of resiliency, and people with near-miss information are less likely to purchase flood insurance. People who escape damage by chance will make decisions consistent with the perception that a situation is less risky. A near-miss can be defined as an "event that had a nontrivial probability of ending badly, but by chance did not". Prior hits increase the likelihood of protective action while prior misses decrease the likelihood of protective action compared to those without near miss information.

Near-miss events discourage people from attending to risk due to some implicit Bayesian updating of probabilities (Dillon et al. 2011).

According to Tinsley et al. (2012), near-miss events can be categorized as vulnerable or resilient. A vulnerable near-miss is where a disaster almost happened and involves perceived vulnerability. A resilient near-miss is where a disaster could have happened and involves perceived resilience; this can decrease mitigation behavior. The narrative that accompanies near-miss facts can impact reactions to hazards. If near-misses can be recognized and interpreted as disasters that "almost happened", that can counteract the "near-miss effect" and encourage mitigation. Vulnerable near-misses involve a negative association and promote risk mitigation (Tinsley et al. 2012).

4.2.1.4 Socioeconomic factors

Socioeconomic factors may influence both risk perception and coping perception. Income has a strong positive influence, while wishful thinking and postponement have a negative influence on implementation of mitigation measures. Social environment, living in a protected area, and income increase the odds of an owner implementing a structural measure (Bubeck et al. 2013). While demographic indicators are generally unreliable predictors of implementation of mitigation measures, they have an effect on perception of hazards and of mitigation measures (Lindell and Perry 2012).

Positive indicators for implementation of mitigation measures include social trust, risk perception, and social economic status (education, income). Negative indicators include psychological vulnerability (powerlessness, helplessness). Trust is critical to acceptance of risk mitigation policies (Lin et al. 2008). According to Bubeck et al. (2012), ownership is important, since tenants have a lower demand for mitigation. Age and level of education have a small or no impact on precautionary behavior. The distance to a water body has little effect on mitigation behaviors. Studies are inconsistent on the role of income and mitigation behavior (Bubeck et al. 2012).

In a study by Botzen et al. (2009), socioeconomic characteristics (including sex, age, and income) had no statistically significant effect on mitigation decisions. Education had a positive and significant effect. The roles of government, risk perception, and geographical characteristics were more important than socioeconomic characteristics (Botzen et al. 2009). In another study, the following demographic factors had a positive impact on risk perception: lower education and income, female gender, and ethnic minority status (Lindell and Hwang 2008).

4.2.1.5 Neighbors and friends

According to a study by Bubeck et al. (2013), people often ignore residual risk, particularly in areas with flood defenses. Examples of neighbors or friends who have implemented a flood mitigation measure have considerable influence on precautionary behavior. If the majority of homeowners in a neighborhood have implemented a mitigation measure, it is likely that others will want to follow suit. Decisions of neighbors can provide important information value. An overlap of household and community measures does occur, but often may be due to the timing of implementation (Bubeck et al. 2013). Research shows that people can learn through their own experiences and also vicariously through others (Dillon et al.

2011). People's mitigation behavior depends partly on neighbors' decisions and actions (Tinsley et al. 2012).

4.2.1.6 Household Mitigation measures

For the implementation of household structural mitigation measures, a study by Poussin et al. (2014) found the most important covariates to be perception of flood damage, perceived self-efficacy, perceived response cost, incentive from insurers, incentives from others, and socioeconomic factors including age and ownership. Feeling of protection by public measures had slightly less importance. For non-structural measures, the most important covariates were found to be perception of flood damage, perceived self-efficacy, perceived response cost, flood experience, and incentives from others. To better prepare households for flooding, the provision of information could be improved, along with improved financial incentives for structural measures (Poussin et al. 2014).

4.2.2 Community Mitigation Measures

According to Brody et al. (2010), there is a strong link between high organizational capacity and implementation of community structural and nonstructural flood mitigation measures. Local organizational capacity includes financial resources, staffing, technical expertise, communication, leadership, and commitment to flood protection. The ability to adjust policies in response to a flooding problem is also important. Organizational capacity is critical for reducing local flood effects (Brody et al. 2010).

Structural flood mitigation measures including levees, dams, and diversions, can be highly effective in mitigating flood damage. As noted by Brody et al. (2010), the limitations of structural approaches include exceedance of design capacity, resulting in significantly higher damages than if unprotected. Channels and levees can raise the river level causing increased flood pulses and velocities downstream. The public often gets a false sense of security associated with public mitigation measures, which can encourage new developments in floodplains. Additionally, structural mitigation measures often have high financial and environmental costs, with dams and other structures causing adverse environmental impacts to fish/wildlife and water quality in hydrologic systems (Brody et al. 2010).

Lands behind levees are generally perceived as protected, and this entices new development. Levees “filter” small floods and change the perception of flood likelihood. This can encourage settlement of marginal lands. This land may be protected from flood events up to a certain level, but vulnerability to large infrequent events increases with development behind levees. For example, an area might be protected from the 100-year flood, but the increased development behind the levee could dramatically increase the losses associated with less frequent but more intense flooding (e.g., the “200-year” event). Residents in these areas may be uninformed that they are in a floodplain for these low-probability but still possible events and therefore unlikely to take any precautionary measures (Ludy and Kondolf 2012). Lacking knowledge about flood risk while under the protection of structural measures, people’s judgments generally depend on their level of trust in risk managers (Terpstra 2011).

Levee systems have also resulted in increasing flood stage in some locations such as the Mississippi River. The average recurrence intervals for major floods are generally much shorter than acknowledged on managed rivers due to increased flood stage (Criss et al. 2001). Clearly, the impact of levees on flood risk extends beyond simple flood elevation changes that are revealed by traditional models.

4.2.3 Agent-Based Models

An Agent-Based Model (ABM) is a stochastic simulation model that includes decision-making entities (agents) in addition to stochastic elements (Bonabeau 2002, Evans and Kelly 2004, Epstein 2006). The agents are autonomous, spatially-explicit, and heterogeneous, and can interact with each other and their environment. They can experience stochastic elements such as flooding events. Agents in an ABM are active and have learning rules that represent how they incorporate new information such as events (e.g., floods) occurring in their environment as well as from messages from other agents. They also have decision rules that specify the actions they can choose and how they choose among their possible actions. Each agent can have distinct values, behavioral rules, and history. An ABM allows simulation of how the behavior of individuals impacts other individuals and a community over time. While ABMs are used to explain, rather than predict, they can be used to simulate the emergence of system-level properties (Crooks and Heppenstall 2012, Berglund 2015).

ABMs have been widely used to examine situations in which individual behavior is an important driver of collective outcomes in ways that cannot be easily modeled by more aggregate models such as system dynamics models. Examples of

ABM applications of this sort include models of civil violence (Epstein 2002), land use change (Evans and Kelly 2004, Magliocca et al. 2011), agricultural decision-making at the farm scale and its impacts on water quality (Ng et al. 2011), and individual level responses to water contamination events and the collective impacts of these individual decisions (Zechman 2011). ABMs have been used to examine coastal flooding by Dawson et al. (2011) with a focus on real-time management of a coastal flooding event, not on the longer time-scales that this study focuses on. Our study focuses on the longer time horizon societal changes (e.g., land use change and household level mitigation decisions) that impact the evolution of flood risk over time.

4.3. Methods and Data

4.3.1 Overview

In our ABM, the agents are households, modeled as land parcels. An annual maximum flood occurs in each year of the 50-year simulation period, and flood risk metrics are recorded annually. The agents can take individual action and can also influence community action. Each agent makes an annual decision about flood risk management actions, as does the community. Flood risk changes over time based on stochastic flood outcomes, individual action, and community action.

As illustrated in Figure 4.1, the model has three main simulation steps. In the first step, an annual flood elevation is simulated, and damage and population at risk are tallied. In the second step, each agent may take action based on risk perception, coping perception, and calculated utility. Potential actions include doing nothing, complaining to the community (requesting community action), elevating mechanical equipment, or elevating the home. In the third step, the community can take action. Actions include doing nothing, putting out an information campaign, or undertaking a structural mitigation project (simulated as a levee). These simulation steps are repeated for each year of the 50-year simulation. The inputs and modeling process for each of the steps are explained in further detail below.

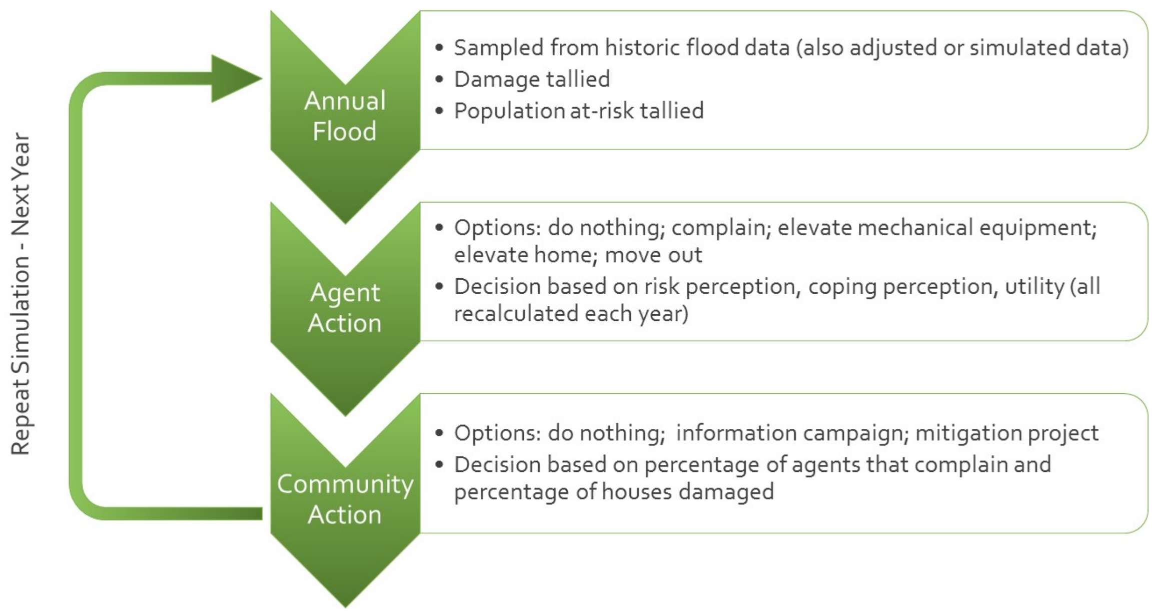

Figure 4.1: Model simulation steps

In order to better understand several key components of the ABM and their influence on the results, four sets of ABM simulations were run. The first was a Base model (Base) wherein agents follow the basic decision rules, but are not able to move in or out, and are not influenced by the flood outcomes or mitigation behavior of their neighbors. In the second model (Land Use or LU), agents may move out of the area if their risk perception reaches a high level, and vacant parcels may be occupied. In the third model (Neighbor or NB), agents may not move in or out of the study area, but are influenced by the flood outcomes and mitigation behavior of their neighbors. For purposes of this study, and due to the relatively small case study area, all agents within the study area are considered neighbors to each other. The fourth model is a combined Land Use and Neighbor model, (LU-NB) where agents may move in or out of the study area, and are influenced by the flood outcomes and mitigation behavior of the other agents.

500 replications were run for each model, and results were recorded. 500 replications were determined to be an adequate number based on convergence calculations (Kelton and Law 2000) on the average damage in the first five simulation years and total damage over the entire simulation period. 500 simulations provide 90% confidence with a relative error of 10%, based on the results of 50 initial simulation runs. Equation 2 shows the convergence calculation used.

$$n_r^*(\gamma) = min\left\{i \geq n: \frac{t_{i-1,1-\propto/2}\sqrt{S^2(n)/i}}{|\bar{X}(n)|} \leq \gamma'\right\} \qquad [2]$$

where: $n_r^*(\gamma)$ = number of simulations required for convergence

n = number of replications for convergence calculation

$S^2(n)$=variance of the mean for n replications

$\overline{X(n)}$= mean damage based on n replications

γ' = adjusted relative error = γ/(1+γ)

4.3.2 Case Study Location

Because flood risk is very location-centric, this study uses a case study approach. The city of Fargo, North Dakota was chosen as the case study location.

Fargo is situated along the Red River of the North and is prone to regular flooding. An area of the city located adjacent to the Red River, consisting of 2,124 land parcels was selected for the study. Extensive GIS data for this area was obtained from the City of Fargo. The case study location is illustrated on Figure 4.2.

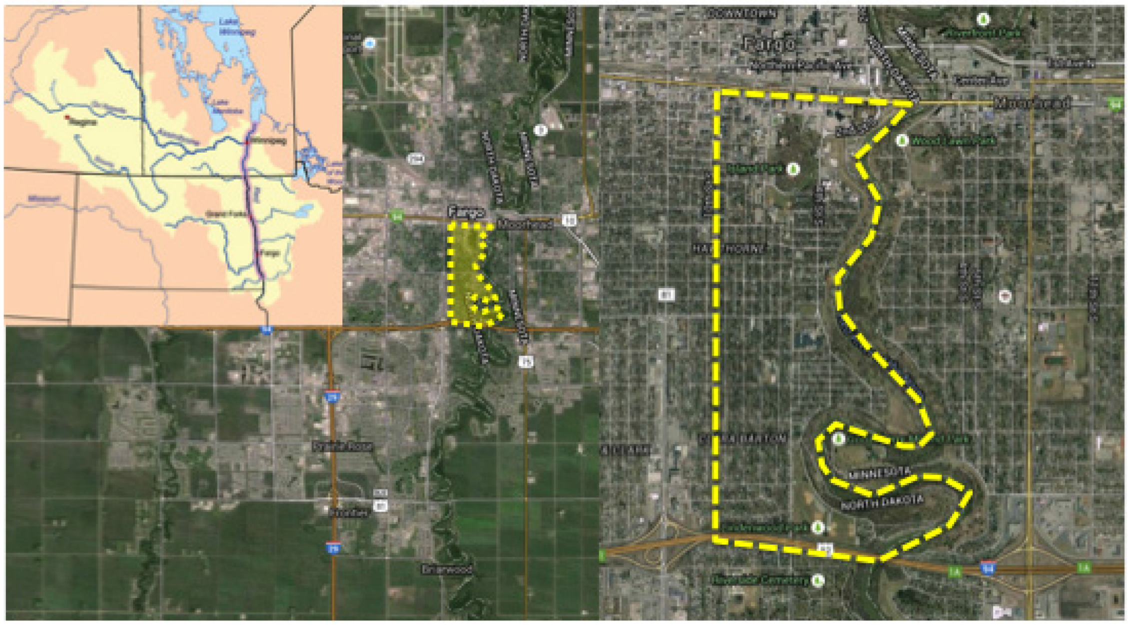

Figure 4.2: Map of case study location

4.3.3 Flood Heights

In the Base Model, the flood heights are sampled from a dataset that was generated using peak annual flood elevations from US Geological Survey (USGS) gauge 05054000 (Red River of the North, Fargo), years 1942-2013. This stream gauge lies close to the midpoint of the river within the study area. Data was available for this gauge from years 1902 to 2013. However, a study by Villarini et al. (2009) indicates that there was a change in the data set starting in year 1942. This is also evident from the parameter codes in the data set. Therefore, only data from years 1942 to 2013 was included in the study, for a total of 72 years of record.

A weibull distribution was fit to the dataset, and the resulting 100-year (0.01 annual chance) flood elevation is 902.5 feet, which is comparable to FEMA's 100-year flood elevation for this location. The maximum flood height in the dataset is 903.5 feet. In order to allow for the evaluation of impacts of a greater magnitude flood in the study area, it was necessary to add a higher flood elevation to the dataset. A 500-year (0.002 annual chance) flood elevation was generated from the weibull distribution, with an elevation of 905.1 feet. The original data set includes 72 years of record. To generate approximately 500 years of record, this data set was replicated 7 times (72x7=504). Then the 500-year elevation was added to the dataset, for a total of 505 flood height data points to sample from in the model. This was chosen rather than generating a fully synthetic data set, so that flood height sample set would mimic real world values.

For scenarios involving community mitigation, the flood data set was altered to represent mitigation. Mitigation was simulated as a levee, and it was assumed that the levee would not fail during the length of the simulation period. Therefore, once community mitigation occurs, the flood elevation set is adjusted by replacing all data points below the mitigation elevation with zero flood elevation.

4.3.4 Agent Behavior

In each year, risk perception and coping perception values are calculated for each agent. If the risk perception and coping perception exceed specified thresholds, the agent will consider taking action to reduce flood risk. The risk perception and coping perception are based on factors identified through the literature review.

A number of factors are included in the calculation of risk perception: prior flood experience (Ludy and Kondolf 2012, Lin et al. 2008, Siegrist and Gutscher 2008), prior near-miss experience (Dillon and Tinsley 2008, Dillon et al. 2011), prior community mitigation (Ludy and Kondolf 2012, Bubeck et al 2013, Birkolz et al 2014), prior agent mitigation (Bubeck et al. 2013), and information (Poussin et al. 2014). For the neighbor models, neighbor flood experience and neighbor near-miss experience are also included (Dillon et al. 2011, Tinsley et al. 2012). Due to the small size of the study area, all agents are treated as neighbors to each other. These factors are presented in Table 4.1. The value of each factor is multiplied by a beta value and summed to generate a total risk perception value. The beta values are positive or negative depending on whether a factor tends to increase or decrease perceived risk. Beta values were chosen to reflect both the magnitude of the factors and the relative weight of the factors. While the literature is explicit qualitatively about important factors that influence flood risk perception, quantitative information is limited. For purposes of this study, the weights were set based on implied importance in the literature and on professional judgment. Flood experience was given double the weight of near-miss experience. Community mitigation, agent mitigation, and information were given equivalent weights. Agent flood and near-miss experiences were given higher weights than neighbor experiences.

The following factor values would result in equivalent magnitude impacts (±20) on flood risk perception: If an agent experiences 1 flood event in 10 years, 2 near-miss events in 10 years, community mitigation project, agent mitigation project, community information campaign, 20% of agents experiencing a flood in 10 years, or 40% of agents experiencing a near-miss event in 10 years.

Table 4.1: Risk perception factors

Factor	**Description**	**Formula**	**Beta**
Flood Experience	Has the agent experienced flooding in previous years?	Number of floods/number of years	200
Near-Miss Experience	Has the agent experienced near-miss events in previous years?	Number of near-miss events/number of years	-100
Community Mitigation	Has the community previously completed mitigation?	Yes (1) or No (0)	-20
Agent Mitigation	Has the agent previously completed mitigation?	Yes (1) or No (0)	-20
Information	Did the community disseminate information in the previous year?	Yes (1) or No (0)	20
Neighbor Flood experience*	Have the agent's neighbors experienced flooding in previous years?	Number of agent floods/(number of years * total number of agents)	1000
Neighbor near-miss experience*	Have the agent's neighbors experienced near-miss events in previous years?	Number of agent near-misses/(number of years * total number of agents	-500

* Neighbor models only

The risk tolerance threshold, the risk perception level at or above which an agent will consider taking action, was set at 60 based on professional judgment. Possible values of the risk perception factors were analyzed to identify the likely threshold at which agents would perceive the risk high enough to consider mitigation action. To simulate agent heterogeneity in risk tolerance, each agent was randomly assigned a risk tolerance adjustment factor between 0.8 and 1.2. The risk threshold was multiplied by this factor so that the threshold was specific to each agent's tolerance value.

In addition to the risk threshold for agent action, there is a risk threshold for agents to move out in the LU and LU-NB models. If the risk reaches this high threshold, the agent will move out, and the parcel becomes vacant. The threshold is set at 90. This threshold is also adjusted by the risk tolerance factor. At the start of each simulation year, there is a probability that each vacant parcel will be occupied. If there is no community mitigation in place, the probability that a vacant parcel will be occupied in a given year is 0.01. If community mitigation is in place, the probability that a vacant parcel will be occupied is 0.1.

Coping perception is calculated similarly. Factors are described in Table 4.2 and include a base value that is randomly assigned to each agent, home value as a proxy for socioeconomic factors (Poussin et al. 2014, Bubeck et al. 2013, Lin et al. 2008), prior agent mitigation (Bubeck et al. 2013), and information (Poussin et al. 2014, Ludy and Kondolf 2012). The NB and LU-NB models also include prior neighbor mitigation (Bubeck et al. 2013, Tinsley et al. 2012). Each of these factors are equally weighted and are assigned a value from 0 to 20. Home value is intended to be a proxy for socioeconomic factors that impact coping perception. The maximum possible coping perception value is 100. The coping threshold is set at 30, based on an analysis of possible values and professional judgment.

Table 4.2: Coping perception factors

Factor	Description	Formula
Base Coping Perception	Random value assigned to each agent	Random value between 0 and 20
Home Value	Value assigned based on property value	<$100,000: 5 $100,000-$125,000: 10 $125,000-$175,000: 15 >$175,000: 20
Prior Agent Mitigation	Has agent previously completed mitigation?	Yes (20) No (0)
Information	Did the community disseminate information in the previous Year?	Yes (20) No (0)
Neighbor Mitigation*	How many of the agent's neighbors have completed mitigation?	<1: 0 1-5: 5 6-10: 10 11-20: 15 >20: 20

*Neighbor model only

Actions include complaining to the community, elevating mechanical equipment, and elevating the house. Each time the coping and risk perceptions meet the specified threshold, the agent complains to the community (requests community action). Additionally, when both the coping and risk perceptions meet the specified thresholds, the agent considers mitigation. The choices of mitigation actions include doing nothing, elevating mechanical equipment or elevating the whole house. A utility function is run and the agent's decision is based on the lowest cost option using the utility function.

4.3.5 Community Action

As stated above, if an agent's risk and coping perceptions meet or exceed the threshold values in a given year, they "complain" to the community. If the number of complaints in a given year equals 5% or more of the agents in the community, the community will undertake an information campaign. Based on conversations with a US Army Corps of Engineers staff member, the USACE provides flood risk and mitigation information to communities on a regular basis. However, communities do not always embark on specific flood risk information campaigns unless somehow prompted to do so. Agents who receive information from the community are more likely to perceive a higher risk of flooding and to undertake mitigation (Lindell and Hwang 2008, Ludy and Kondolf 2012).

If the total community flood damage exceeds $10 million in a given year, the community will complete a flood mitigation project. In this study, the mitigation project is modeled as a flood barrier/levee project. A depth-damage curve was generated for the entire community, and the $10 million threshold was selected as the point on the curve in which damage begins to increase somewhat sharply. This corresponds to the flood elevation where damage is significant enough to warrant community action.

4.3.6 Climate Scenarios

Future climate scenarios are based on a US Army Corps of Engineers report (Alberto et al. 2015). The report includes tables and figures showing the estimated climate change impact on the frequency curve for the periods 2011-2040, 2041-2070, and 2071-2100. For each time range, the increase in median, 10%, and 90% values are provided. The 2041-2070 time range estimates were chosen for use in the ABM project. A table in the report (reproduced below in Table 3) provides the median, and 10%, and 90% limits of the frequency curve values for this time range.

Based on the report values, we computed a percent change for each of the return periods, for the median, 10%, and 90% estimates, as shown in Table 4.3. Then we calculated a set of flow values for the median, 10%, and 90% scenarios, based on the original set of flow values and the percent change values for each scenario. Percent change values for each flow rate were interpolated based on the percent change values specified for the return periods. In other words, sets of flow values were generated for the median, 10%, and 90% scenarios. Using the rating curve for gauge 05054000, flood heights were estimated for each of these flow values. In some cases, the flow values exceeded the maximum flow on the rating curve. The upper portion of the rating curve (from approximately 15,000 cfs to the maximum value of 33,000 cfs) is nearly linear, and we assumed that the linear trend continued beyond the maximum value on the rating curve. This linear equation was used to estimate flood heights for flows above the maximum flow value.

Table 4.3: Period 2041-2070 future climate percent change

Exceedance Probability	**Return Period**	**% Change Median**	**% Change 10%**	**% Change 90%**
0.5	2-yr	13%	-22%	58%
0.1	10-yr	5%	-17%	35%
0.02	50-yr	4%	-23%	56%
0.01	100-yr	6%	-24%	63%
0.005	200-yr	9%	-28%	70%

4.3.7 Sensitivity Analysis

Because of the subjective nature of several key parameters in the study, extensive sensitivity analysis was performed on those parameters. Parameters included risk perception threshold, coping perception threshold, agent complaint threshold, and community damage threshold. Additionally, for the Land Use and LU-NB models, sensitivity analysis was performed on the risk threshold for moving, the probability of a vacant parcel being occupied without community mitigation, and the probability of a vacant parcel becoming occupied after community mitigation. For the sensitivity analysis, a single parameter was adjusted at a time, with 500 replications run for each adjustment. The resulting damage values were plotted and are included as Appendix A. For the land use models' sensitivity analysis, average vacancy was plotted in addition to the damage values.

4.4. Results

4.4.1 How does flood risk change over time?

Figures 4.3a and 4.3b illustrate the average annual damage (average of 500 simulations) for each of the models over the 50-year simulation period. Average annual damage declines over time due to the influences of agent mitigation, community intervention, and movement in and out of at risk areas. The Base model generally has the highest annual average damages. The neighbor and LU-NB models generally have the lowest annual average damages, and the LU model seems to exhibit the greatest fluctuation in annual damage.

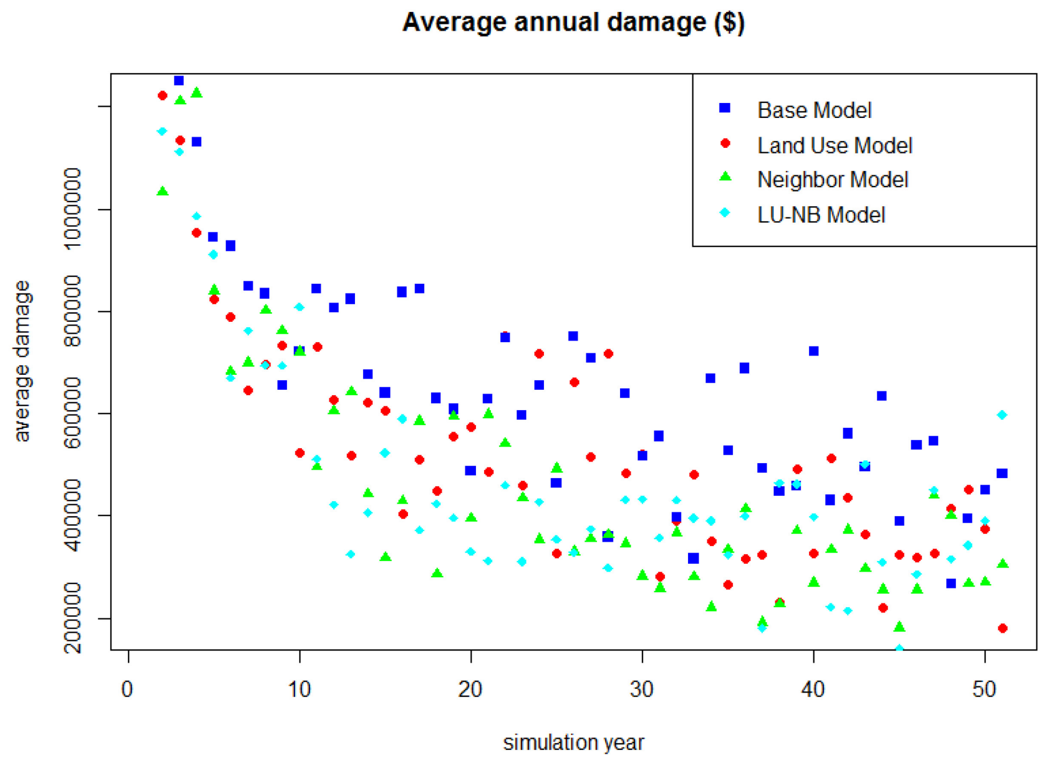

Figure 4.3a: Average annual damage

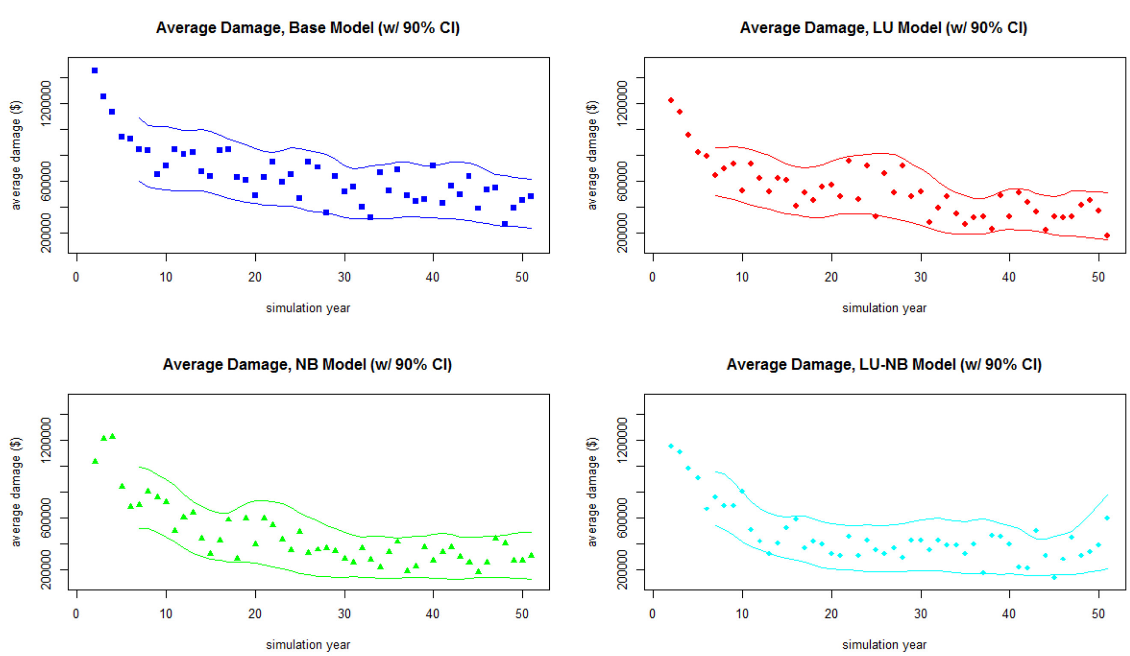

Figure 4.3b: Average annual damage

In the LU model, agents can move in and out of the study area. Damages for this model decrease along with the other models initially, but then increase for some of the middle years due to agents moving back into the study area. This model has slightly wider 90% confidence bounds in the middle years due to variations in movement in and out of the study area. For instance, in year 25, the confidence bounds for the LU model span a damage range of about $640,000 versus $520,000 for the Base model, $380,000 for the NB model, and $360,000 for the LU-NB model.

The neighbor models generally have lower average annual damage than the Base or LU models. Neighbor flood events tend to increase an agent's perceived risk, while neighbor near-miss events tend to decrease an agent's perceived risk. Coping perception is positively affected by neighbor mitigation, which leads to higher numbers of agents mitigating and moving out of the study area. The LU-NB results tend to fall in between the results of the LU and the NB models.

Figure 4.4a shows a density plot of the total damage for each of the four models, based on 500 simulations each. In evaluating the density plot, it appears that the LU model simulations tend to have lower total damages than the other simulations, followed by the NB model and the LU-NB model. The lower total damage for the LU model seems to be driven by lower average annual damages in the early years of the simulation and increasing vacancy rates. The Base model simulations are more likely to have higher total damages.

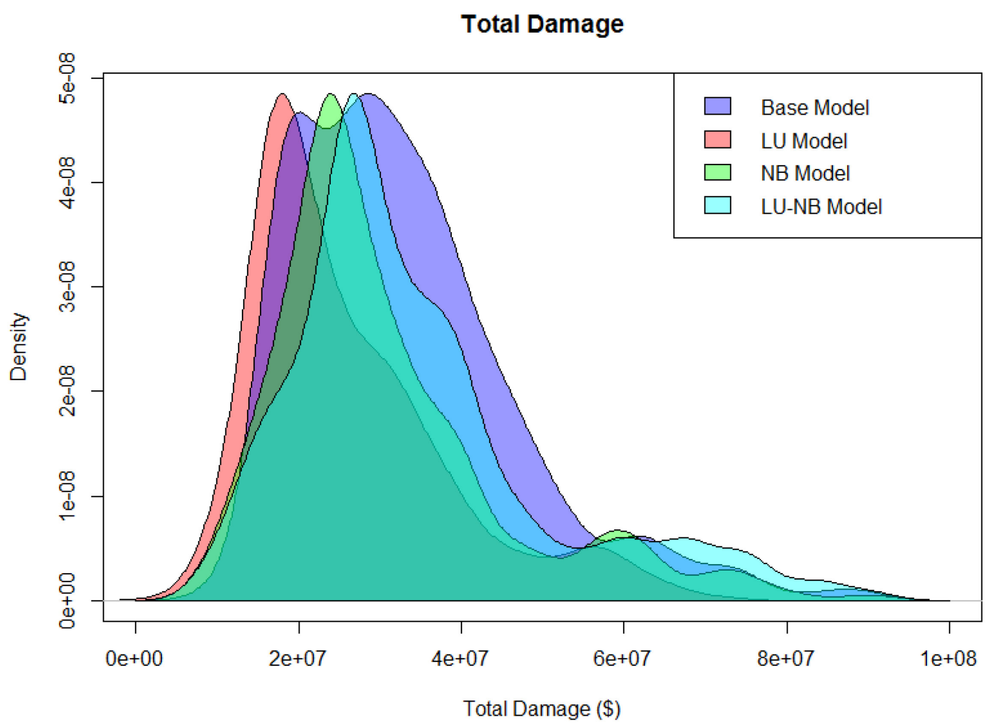

Figure 4.4a: Density plot of total damage

Total damage evaluated on a per capita basis (Figure 4.4b) differs from the total damage results in several ways. In reviewing total damage, the LU model tends to have the lowest damage, followed by the NB model, and then the LU-NB model. However, on a per capita basis, the LU-NB model tends to have the lowest total damage, followed very closely by the LU model, and then the NB model. In the land use models, the agents at highest risk tend to be the ones that move out, resulting in lower per capita damages. Typical values of total per capita damages for the Base model span a wider range than the other models, as do typical values of total damages for the Base model. In some runs, total per capita damages are lower for the Base model than for the NB model. This is likely due to increased agent mitigation in the NB model, which can lead to decreased community mitigation. In general, total per capita damage for the NB model is less than that for the Base model. Decision makers may want to consider per capita damages instead of total damages if they are interested in keeping a community intact and vibrant versus solely minimizing flood risk. The per capita damage is also more relevant for homeowner level insurance claims. Our model accounts for risk only within the study area, and does not consider any risk incurred by agents that move out of the study area.

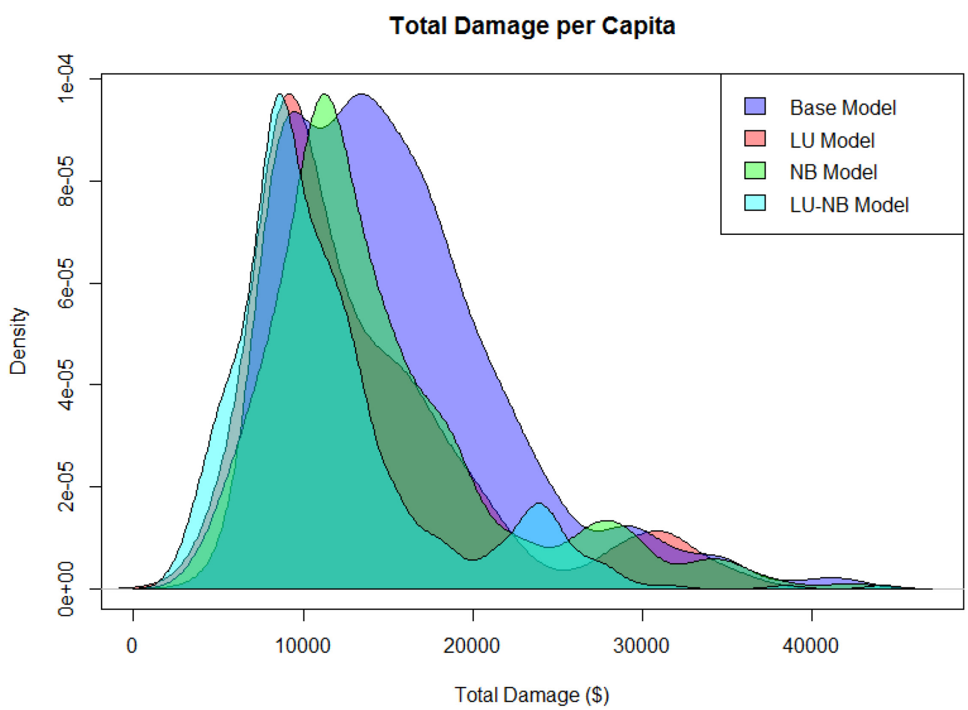

Figure 4.4b: Density plot of total per capita damage

As shown on Figure 4.5, the Base model and Land Use model have low numbers of agents mitigating in all simulations, ranging from around 0 to 30 agents. The NB and LU-NB models have more agents mitigating, with many NB simulations having 300 to 400 agents mitigating and many LU-NB simulations having 200 to 300 agents mitigating. More agents mitigate in the neighbor models due to increased coping perceptions associated with other agents mitigating. The LU-NB model has less agent mitigation than the NB model due to agents choosing to move out, and therefore, not mitigate.

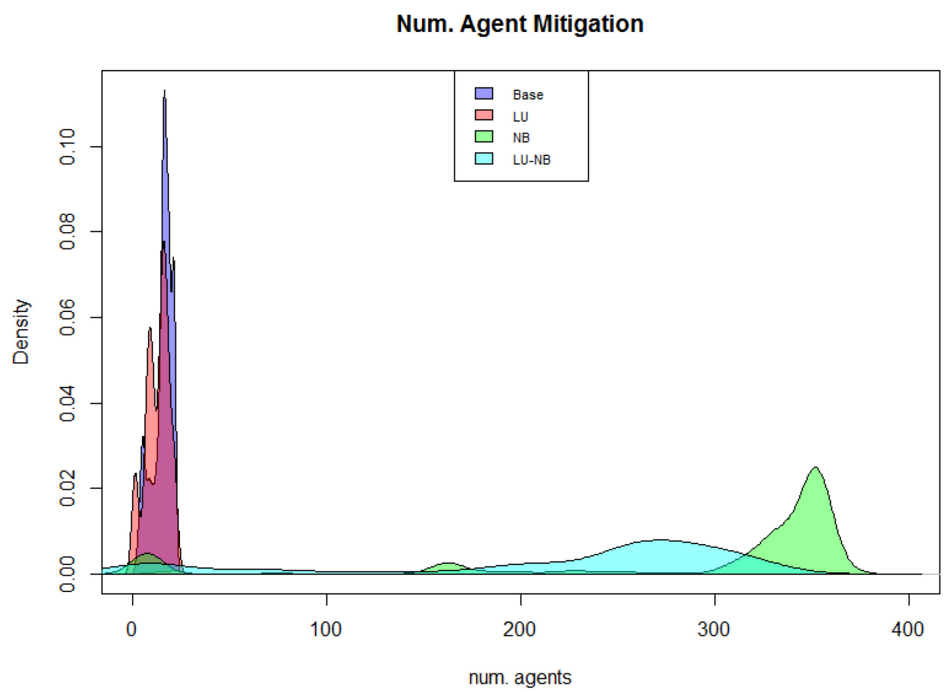

Figure 4.5: Density plot of agent mitigation

4.4.2 How does community action affect risk?

Figure 4.6 shows the total damage for runs with and without community mitigation for each of the four models. These histograms show that the runs with community mitigation generally have lower damages than those without community mitigation. However, for all four of the models, the runs with the highest damages are those with community mitigation. In evaluating this figure, it was unclear whether this was because community mitigation is triggered by damaging flood events, or because once community mitigation is installed, risk perception declines and agents tend not to undertake individual mitigation action. To further explore the reasoning, the total damage before and after mitigation was tabulated and is included in Table 4.4. In reviewing this table, it is clear that average annual damage is much lower after community mitigation than before mitigation, as should be expected since there is no damage in most years after mitigation. The maximum damage in any individual year before community mitigation is typically higher than the maximum annual individual year damage after community mitigation for each of the four models when evaluating the simulations as a whole. However, for some individual simulations, the highest damage year occurs after community mitigation is in place. These results indicate that in general, damage is significantly reduced after community mitigation. In some instances, high elevation floods occur after mitigation and exceed the mitigation height, resulting in very high damages.

Table 4.4: Summary of Damage before and after community mitigation

Model	**Avg. Year of Community Mitigation**	**Avg. Annual Damage Before Community Mitigation**	**Avg. Annual Damage After Community Mitigation**	**Max. Annual Damage Before Community Mitigation**	**Max. Annual Damage After Community Mitigation**
Base	22.7	$3,678,384	$72,242	$88,636,114	$44,631,991
LU	18.7	$3,431,480	$30,407	$72,062,866	$40,593,226
NB	16.1	$4,452,000	$41,990	$77,672,006	$45,970,167
LU-NB	18.6	$4,158,000	$36,710	$67,925,311	$41,196,200

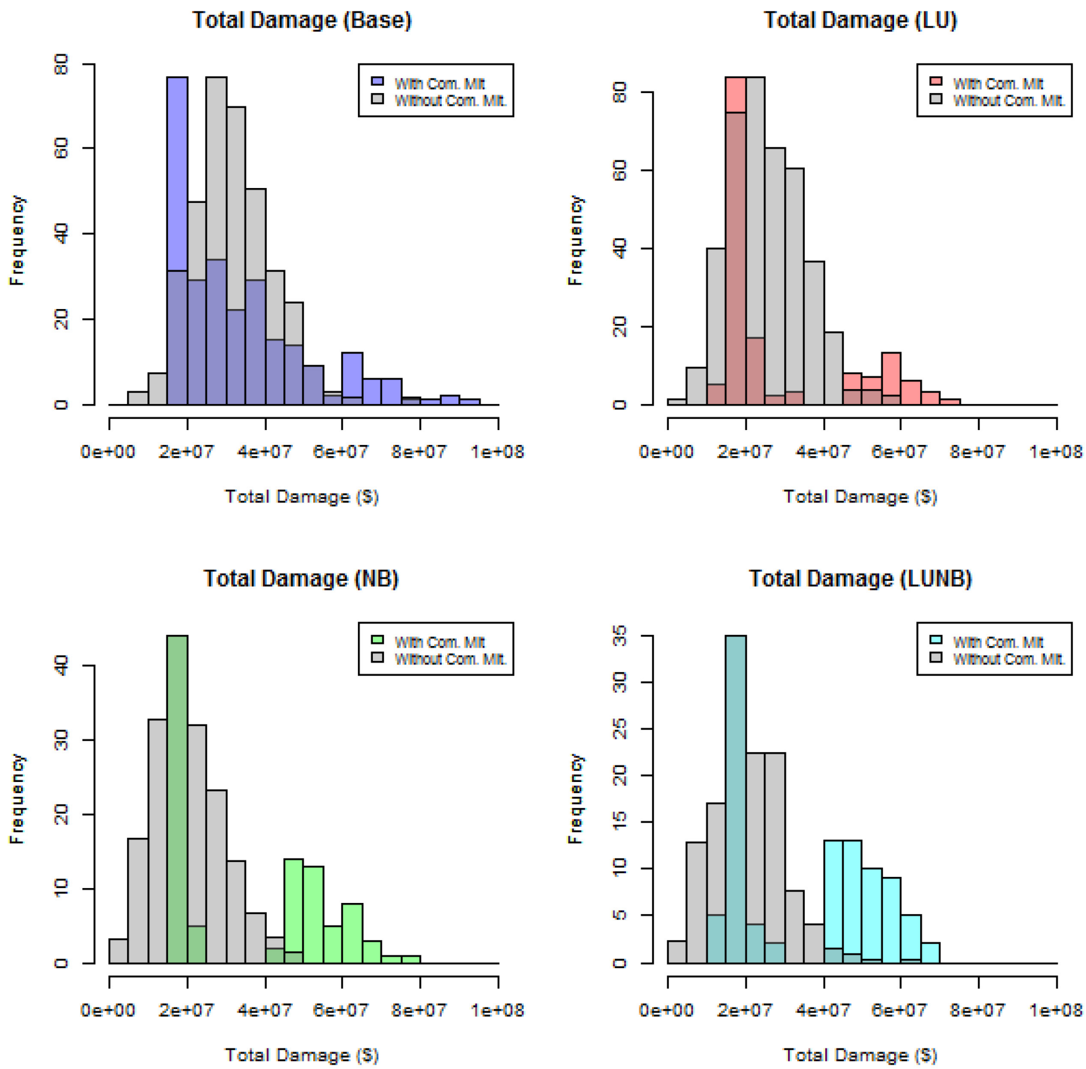

Figure 4.6: Damage with and without community mitigation

In order to further understand the influence of community mitigation, the four models were run under historic climate conditions with the possibility of community mitigation disabled in the simulation. Table 4.5 shows average total results with and without the potential for community mitigation. For all of the models, the average total damage is higher without the potential for community mitigation. The difference is much greater for the Base model, where agents do not have the option to move out, and there is no neighbor influence on agent mitigation.

The average number of agents mitigating is higher without the potential for community mitigation, which may offset some of the damage associated with the lack of community mitigation. While the costs of community mitigation are not evaluated in this study, the difference in average total damage with and without community mitigation may not be substantial enough in some cases to compensate for the cost of a community mitigation project.

Table 4.5: Damage and agent mitigation without community mitigation (CM)

	Avg. Total Damage		**Avg. Agent Mitigation**	
	With CM	**Without CM**	**With CM**	**Without CM**
Base	$32.48M	$43.6M	15	41
LU	$26.14M	$28.8M	12	22
NB	$23.17M	$25.8M	292	315
LU-NB	$23.40M	$24.6M	219	233

4.4.3 How does individual behavior affect risk?

The maps in Figure 4.7a illustrate property value and parcel elevation for each agent. Figures 4.7b-4.7e show total damage and agent mitigation for each individual agent, as well as vacancy in the final simulation year (year 51) for the land use models. The total damage is presented as a percentage of property value (total damage divided by property value), and agent mitigation is shown as the percentage of simulations where the agent mitigated. Damage and mitigation do occur in areas that are not adjacent to the river, and it is assumed that all areas are hydraulically connected, based on the prevalence of low-lying roads in the study area.

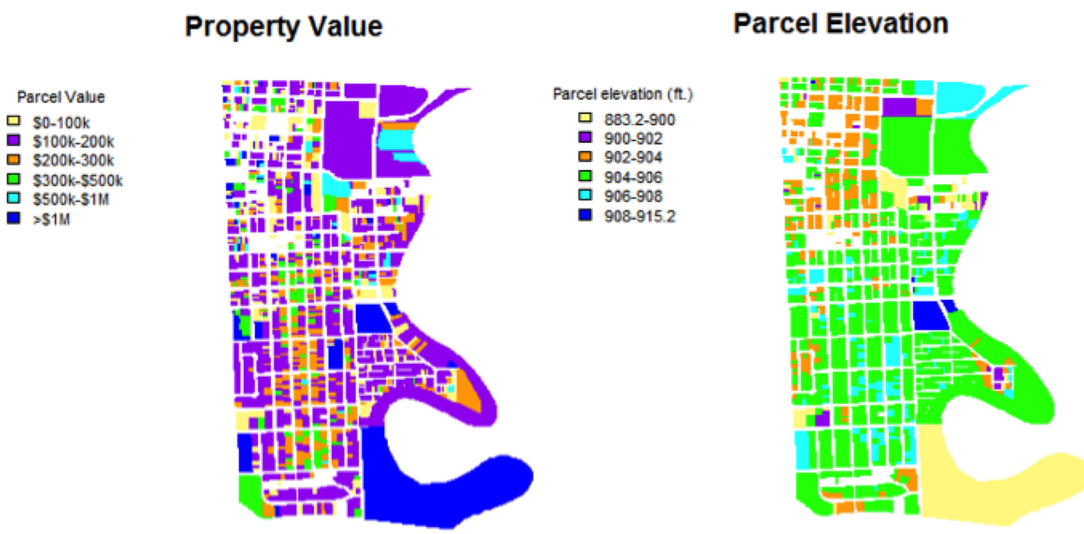

Figure 4.7a: Maps of Parcel Properties

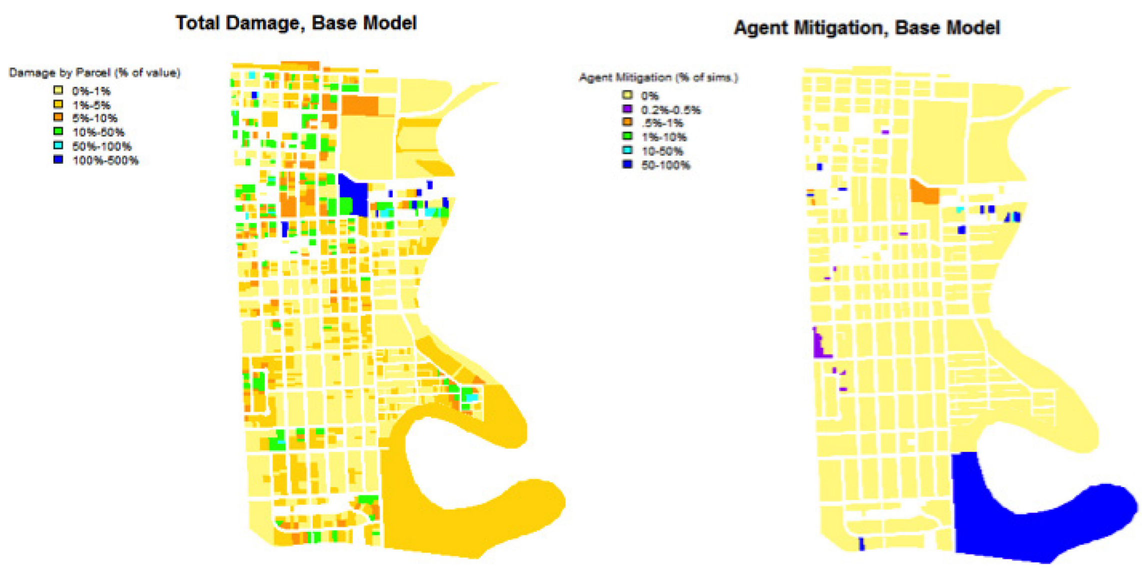

Figure 4.7b: Maps of Base model results

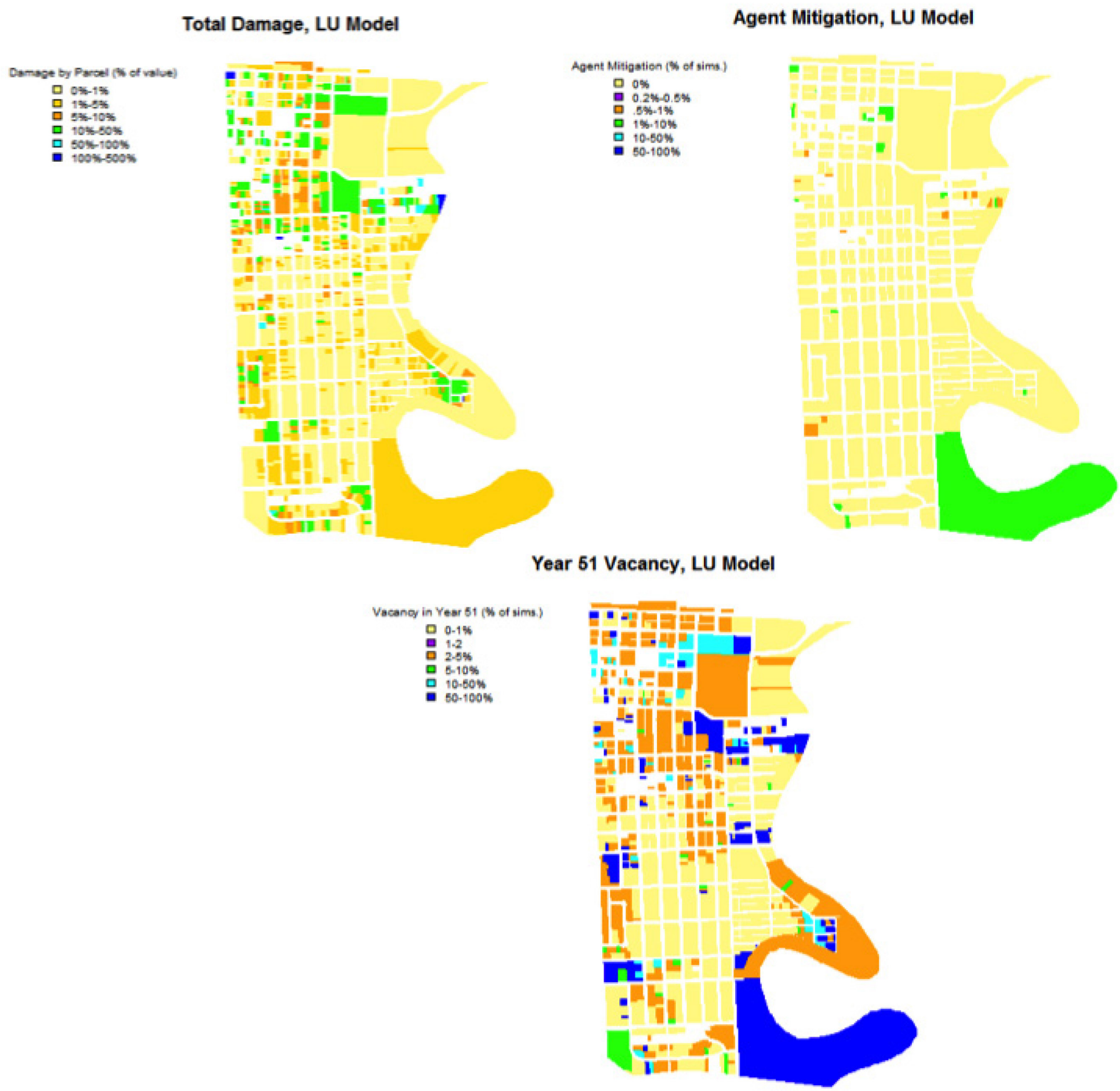

Figure 4.7c: Maps of Land Use model Results

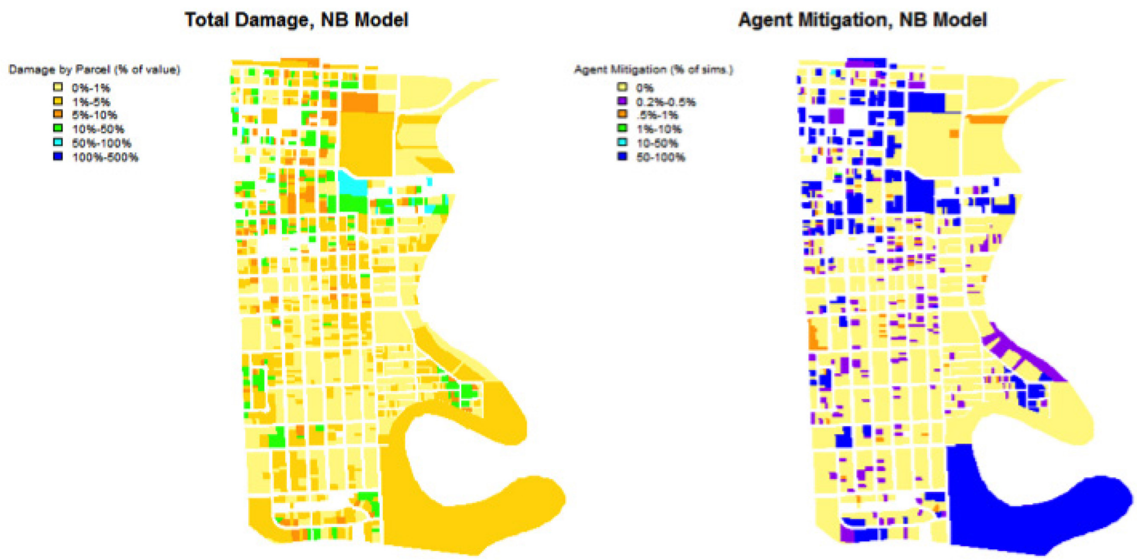

Figure 4.7d: Maps of Neighbor model Results

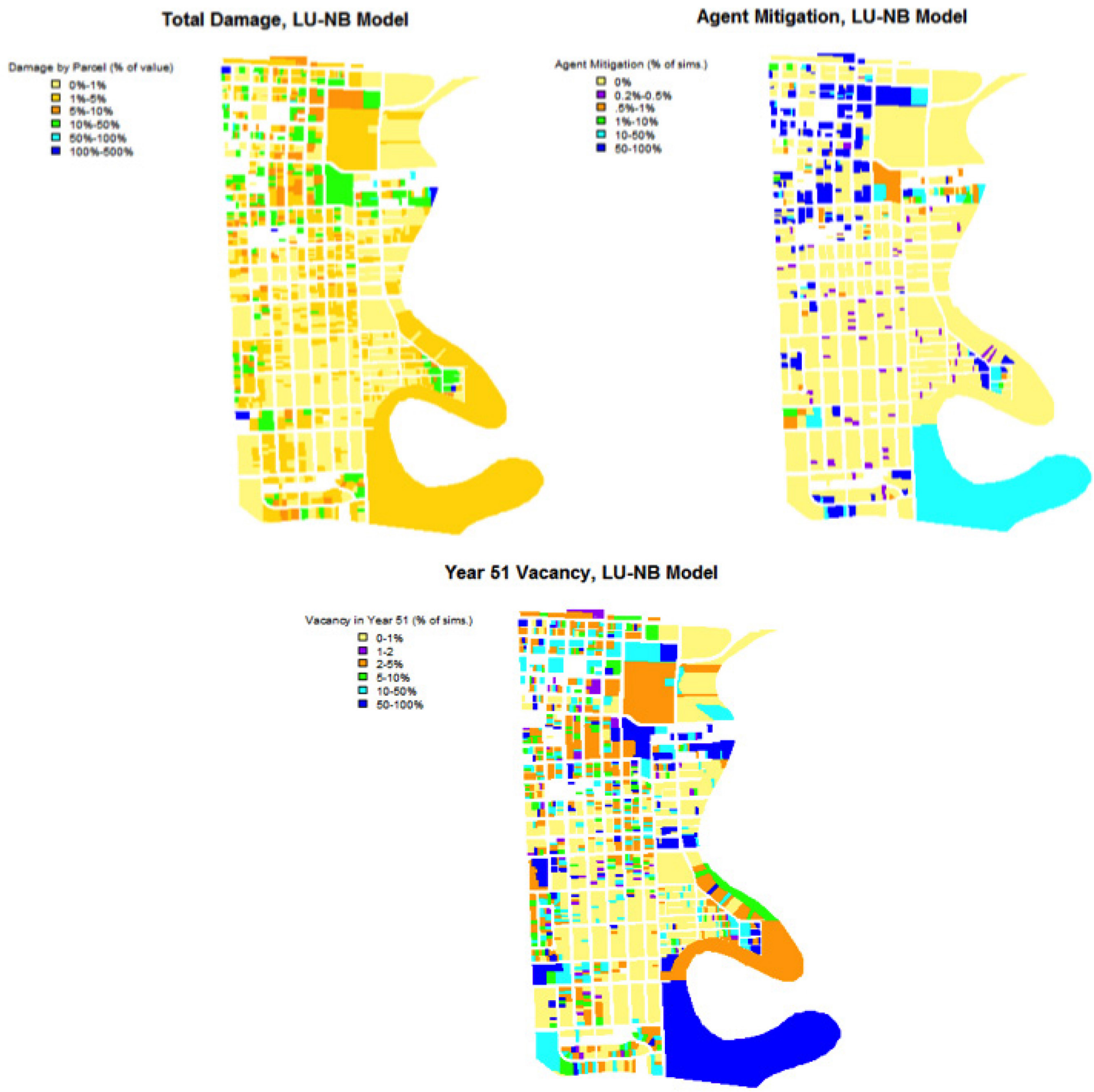

Figure 4.7e: Maps of Land Use-Neighbor Results

Agent mitigation is very limited in the Base and LU models, and much more prevalent in the NB and LU-NB models. This is due to the influence of neighbors on agents, particularly the increase in coping perception associated with neighbors taking mitigation action. In evaluating the plots, it is clear that lower elevation agents install mitigation measures more frequently than higher elevation agents. Much of the agent mitigation is clustered in the northwest portion of the study area, where the parcels tend to have elevations in the range of 902 to 904 feet, and in lower lying areas along the river. The same agents tend to mitigate in each of the four models due to agent characteristics.

Total damage is generally highest in low lying parts of the study area, including the northwest area, portions along the river, and some areas along the western and southern borders of the study area. The central to south central portion of the study area seems to have the lowest total percent damage. This area also has higher property values, in general, than other portions of the study area, and some parcels within this area have higher elevations.

In general, the vacancy rate in the final simulation year is highest in portions of the study area that had higher damage values, as described above. In studying results for individual agents, some with very high vacancy percentages have very low damage percentages. This indicates that agents act preemptively based on high risk and coping perceptions. For instance, the agent located in the southwest corner of the study area, with moderate to high property value and elevation, has a vacancy rate in the 5-10% range for the LU model and 10-50% in the LU-NB model, with damages in the 0-1% range for each.

Initially, 5% of the study area is vacant. Figures 4.8a and 4.8b illustrates how vacancy changes over time in the land use models. In the LU model, vacancy generally increases slightly from the initial rates in the middle and late years of the study, with certain simulation runs having much higher vacancy rates than the rest. In the LU-NB model runs, the increase in vacancy rates is more pronounced. In many runs, vacancy increases in the middle years, and then decreases slightly in the late years.

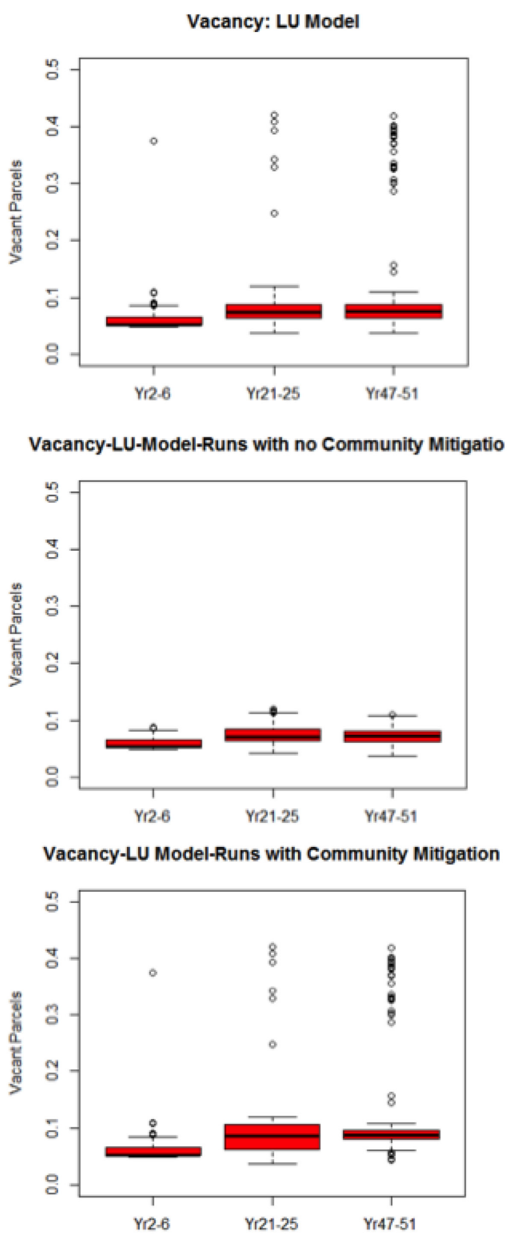

Figure 4.8a: Vacancy, Land Use Model

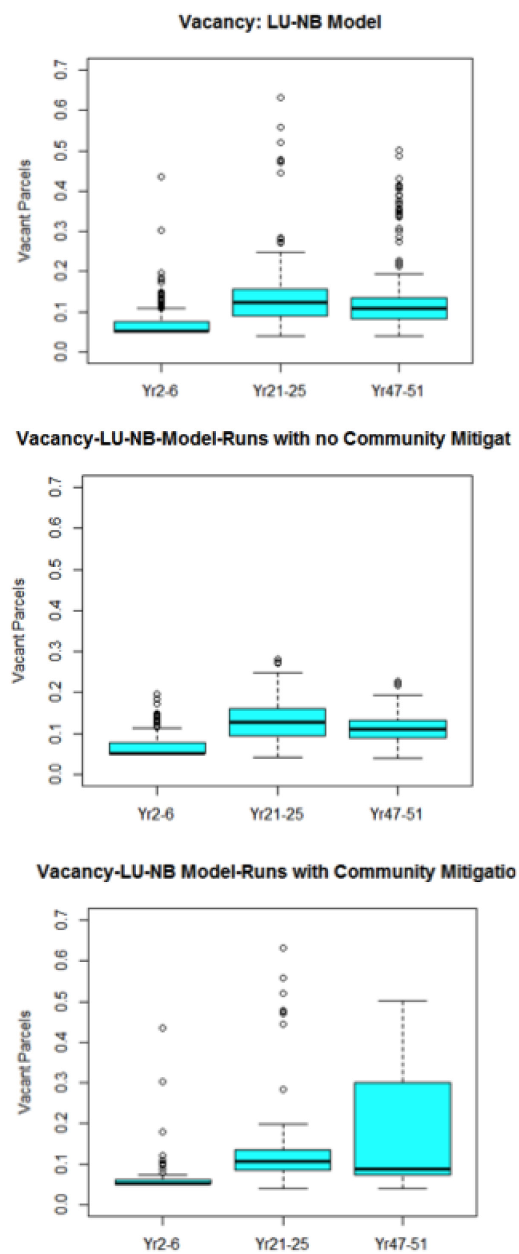

Figure 4.8b: Vacancy, LU-NB Model

4.4.4 Future Climate

Each of the four models was run under historic climate and three future climate scenarios, with results presented in Table 4.6. Damage under the 10% climate scenario was well below the historic and median climate scenarios, while damage under the 90% climate scenarios was nearly an order of magnitude higher than the historic scenario.

While the future climate scenarios are uncertain, some interesting results are evident. The median climate scenario has higher average annual damage than the historic climate scenario in the early years. However, in the middle years, the median climate damage is lower than the historic climate damage for the Base and NB models. In the late years, damage is lower for all four models under the median climate scenario than under the historic climate scenario. Total damage for the Base model is lower for the median climate than for historic climate scenario. These results indicate that in some cases, climate change may result in increased risk perception and increased agent and community mitigation, resulting in lower total damage than under historic climate scenarios.

The 10% climate and 90% climate scenario results are very different than historic and median results, but like those models, average annual damage declines over time. Total 90% climate damage is significantly less under the LU and LU-NB models than under the other models due to the high percentage of agents moving out in those models. The 90% climate results in very high risk perception leading to high vacancy rates.

In general, these results indicate that moderate increases in flood heights due to climate changes may be managed through agent and community action. Very large increases in flood heights result in extremely high damage values, despite agent and community efforts to mitigate, and damages remain high despite high percentages of agents moving out of at-risk areas. Under the 10% climate scenario, damages are significantly less than under historic climate. Even with lower flood heights, risk declines over time, primarily due to individual agent mitigation at high-risk parcels.

Table 4.6: Damage under future climate scenarios ($ millions)

	Historic Climate	**Median Climate**	**10% Climate**	**90% Climate**
Avg. Annual Damage (Yrs 2-6)				
Base	$5.70	$7.43	$1.93	$44.32
LU	$4.92	$6.49	$1.97	$40.03
NB	$4.99	$7.45	$2.02	$45.01
LU-NB	$4.83	$6.45	$1.80	$47.32
Avg. Ann. Damage (Yrs 21-25)				
Base	$3.09	$2.47	$1.38	$20.72
LU	$2.74	$2.82	$0.60	$14.57
NB	$2.42	$2.05	$0.48	$16.01
LU-NB	$1.87	$2.41	$0.53	$10.01
Avg. Ann. Damage (Yrs. 47-51)				
Base	$2.14	$1.09	$1.28	$9.03
LU	$1.75	$1.73	$0.46	$5.25
NB	$1.69	$1.63	$0.21	$8.11
LU-NB	$2.10	$1.62	$0.36	$8.11
Total Damage				
Base	$32.48	$30.49	$14.24	$218.76
LU	$26.14	$30.71	$7.79	$160.44
NB	$23.17	$27.26	$6.10	$207.66
LU-NB	$23.40	$26.13	$7.01	$144.01

It is clear that agent movement out of the study area has a strong influence under some of the future climate scenarios. Table 4.7 provides a summary of vacancy rates in the land use models. The starting vacancy rate in the models is 5.2%, which remains the vacancy rate for the entire simulation in the Base and NB models. Under historic climate, average vacancy over the simulation period is 8% in the LU model and 12% in the LU-NB model. Vacancy rates are slightly higher under the median climate scenario, and substantially increased under the 90% climate scenario, with average vacancy rates of 52% for the LU model and 68% for the LU-NB model.

Table 4.7: Vacancy Rates for Land Use Models, Future climate scenarios

	Historic Climate	**Median Climate**	**10% Climate**	**90% Climate**
Avg. Vacancy Rate (Yrs. 2-6)				
LU	6.0%	6.0%	5.5%	14.3%
LU-NB	6.7%	7.3%	5.5%	19.5%
Avg. Vacancy Rate (Yrs. 21-25)				
LU	8.0%	11.3%	6.0%	56.6%
LU-NB	13.3%	16.6%	5.8%	73.4%
Avg. Vacancy Rate (Yrs. 46-51)				
LU	9.0%	13.1%	5.4%	65.6%
LU-NB	12.2%	17.2%	5.3%	85.8%
Avg. Vacancy Rate (Yrs. 2-51)				
LU	8.0%	10.9%	5.8%	51.8%
LU-NB	11.9%	15.5%	5.6%	68.2%

Base Vacancy Rate = 5.2%

Due to the high vacancy rates in some cases associated with the future climate scenarios, total damages were also evaluated on a per capita basis, as presented in Table 4.8. Per capita future climate damage results are similar to the total damage results in that the damage in the early years is higher for the median climate scenario than the historic climate scenario. In the middle and later years, median climate damage is generally comparable to the historic climate values or less than the historic climate values. For all climate scenarios, the average total per capita damage is lowest for the NB model. In evaluating the total per capita damage values for the median and 90% climate scenarios, the LU and LU-NB models have higher per capita total damage than the other models. The elevated flood risk causes more agents to move out in those models. This leaves a lower number of agents remaining in the community, resulting in less influence from neighbors for agent mitigation and reduced demand for community mitigation measures.

Table 4.8: Per Capita damage under future climate scenarios ($)

	Historic Climate	**Median Climate**	**10% Climate**	**90% Climate**
Avg. Annual Damage (Yrs 2-6)				
Base	$2,834	$3,691	$957	$22,019
LU	$2,465	$3,252	$983	$21,995
NB	$2,478	$3,702	$1,006	$22,363
LU-NB	$2,438	$3,275	$897	$27,669
Avg. Ann. Damage (Yrs 21-25)				
Base	$1,539	$1,227	$684	$10,291
LU	$1,403	$1,496	$301	$15,787
NB	$1,202	$1,016	$239	$7,952
LU-NB	$1,012	$1,363	$267	$17,701
Avg. Ann. Damage (Yrs. 47-51)				
Base	$1,063	$540	$636	$4,486
LU	$904	$940	$228	$7,183
NB	$836	$812	$102	$4,029
LU-NB	$1,124	$917	$178	$6,515
Total Damage				
Base	$16,137	$15,145	$7,073	$108,678
LU	$13,376	$16,235	$3,893	$156,747
NB	$11,510	$13,540	$3,031	$103,164
LU-NB	$12,510	$14,553	$3,501	$213,546

4.4.5 Sensitivity Analysis

Due to the uncertain nature of several model input assumptions, sensitivity analysis was performed to evaluate the influence in changes to these parameters. Plots of the sensitivity analysis results are included as Appendix B.

Risk Threshold: The standard value of Risk Threshold is 60, and the value was varied between 40 and 80 for the sensitivity analysis runs. Lower values of risk threshold may result in more agent mitigation and complaints. Damage is relatively consistent as Risk Threshold varies between 50 and 80. However, both damage and mitigation results are highly sensitivity to variations in this input in the range of 40 to 50. Agent mitigation is much higher for a Risk Threshold of 40 than for higher values, which results in less community mitigation and lower damage values.

Coping Threshold: The standard value of Coping Threshold is 30, and the value was varied between 10 and 50 for the sensitivity analysis runs. Lower values of coping threshold may result in more agent mitigation, complaints, and movement out of the study area (in the land use runs). Damage was somewhat sensitive to changes in Coping Threshold, with particular sensitivity to lower values of Coping Threshold. The model runs with a low Coping Threshold had higher values of agent mitigation and lower values of community mitigation. The additional agent mitigation results in less pressure for community mitigation. Compared to the other parameters, the model results seem most sensitive to changes in the Coping Threshold.

Complaint Threshold: The complaint threshold was varied from 42 to 170, and the standard value is 106, equivalent to 5% of the agents. The complaint threshold impacts whether or not the community will put out an information campaign in a given year. Damage, agent mitigation, and community mitigation are all fairly insensitivity to variation in the complaint threshold.

Damage Threshold: The damage threshold was varied from $6 million to $14 million, with a standard value of $10 million. The damage in the early years is fairly insensitive to the damage threshold. The damage in the middle years and late years are slightly more sensitive to the damage threshold, and the total damage is more sensitive, particularly for the Base Model. Community mitigation is highly sensitive to the damage threshold, which is intuitive since the damage threshold directly impacts community mitigation. Agent mitigation is fairly insensitive to damage threshold for the Base and LU models, which tend to have low agent mitigation, but is more sensitive for the neighbor models. As the Damage Threshold for community mitigation increases in the lower range, agent mitigation tends to increase. Agent mitigation is less sensitive to changes in the higher range of this parameter.

Move Threshold: Risk Threshold for Moving was varied between 75 to 110, with a base value of 90. The vacancy rate was sensitive to this parameter for the LU-NB model, but not for the LU model. This may be because coping threshold tends to be higher in the LU-NB model, resulting in more movement out of the study area. In that model, as the Risk Threshold for Moving increases, the vacancy rate declines.

Probability of Moving In (without community mitigation): The probability of vacant parcels being occupied without community mitigation was varied from 0.004 to 0.08, with a standard value of 0.01. The vacancy rate was sensitive to this parameter in the early years, but was considerably more sensitive in later years, with vacancy steadily declining as the probability of moving in increases.

Probability of Moving in (with community mitigation): The probability of vacant parcels being occupied after community mitigation was varied from 0.04 to 0.16 with a standard value of 0.1. Vacancy was fairly insensitive to this parameter.

Sensitivity analysis was also run for the Base model future climate scenarios. Plots are presented in Appendix C. In reviewing these plots, sensitivity for the median and 10% climate were very similar to that for the historic climate. Sensitivity was more pronounced for the 90% climate scenario, particularly for Coping Threshold, likely due to the higher magnitude values associated with the

90% climate scenario. Based on the similarity of the climate change sensitivity results to the non-climate change sensitivity results for the Base model, sensitivity analysis was not performed for the LU, NB, and LU-NB models under the climate scenarios. In developing a more detailed model of climate change impacts to evolving flood risk, particularly for scenarios with extreme increases in flooding, a more extensive sensitivity analysis would be needed, particularly for the Coping Threshold parameter.

4.5. Strengths and Limitations of Agent-Based Models

ABMs are generally useful for applications where interactions between agents are complex. They are well suited to systems where space is crucial, the population is heterogeneous, the topology of agents is heterogeneous and complex, and where agents exhibit complex behaviors such as learning and adaptation (Bonabeau 2002). While ABM is a useful tool for simulating some types of complex systems, there are a number of commonly recognized challenges and limitations associated with ABMs. The first is that an ABM needs to serve a certain purpose and the level of detail employed needs to match that purpose (Bonabeau 2002, Crooks et al. 2008, Crooks and Heppenstall 2012).

Another challenge with ABMs is that behavioral rules can be difficult to specify and quantify. There can be many different types of behavioral models, and behavioral rules can be empirical or heuristic, psychosocial or cognitive, or assumption-based (An 2012). Human agents often exhibit irrational behavior, complex psychology, and subjective choices, which makes the behavioral rules very hard to quantify and calibrate (Bonabeau 2002, Crooks and Heppenstall 2012).

It is also important to consider the varying degrees of accuracy in the input and output of an ABM. ABMs provide a range of accuracy in results that in some cases provide output only suitable for qualitative usage and in other cases can provided detailed quantitative results that can be suitable for decision-making (Bonabeau 2002). ABMs are typically useful for simulating emerging, system-level trends, but their use for prediction can be challenging. ABM results can be sensitive to initial conditions and small variations in behavioral rules (Crooks and Heppenstall 2012). Because of this, ABMs are generally more useful as research tools than as operational decision support tools (Matthews et al. 2007).

The complex nature of ABMs makes them difficult to verify, and good models require extensive testing to be sure that the rules are working as intended. Model validation and calibration can also be challenging. Furthermore, due to complexity, the models can be very computationally intensive and time consuming to generate and run (Crooks et al. 2008, Crooks and Heppenstall 2012, Bonabeau 2002). The spatial nature of many ABMs makes the model results easy to communicate and share. However, it can be difficult to explain the model structure and components (Crooks et al. 2008).

Clearly, there are considerable challenges and limitations associated with ABMs. However, for some systems with complex interactions between humans and the environment, ABMs are the only available simulation method (Bonabeau 2002). ABMs have the distinct advantage of allowing the modeling of interactions between individual decision-makers with each other and their environment. They allow social processes and the non-monetary aspects of decision-making to be coupled with models of the physical environment in a dynamic way. They can be used to simulate the emergence of collective responses to policies and to evaluate the robustness of a policy (Mathews et al. 2007). Despite the challenges associated with ABMs, they provide a unique solution to simulating the interactions between humans and their environment for applications such as the evolution of flood risk in a community.

4.6. Conclusions

This study presents a new modeling approach for simulating the evolution of community flood risk. An agent-based model is used to simulate the influence of individual behavior on community flood risk. Barring influences like population and climate change, flood risk tends to decline in a community over time due to agent and community mitigation. Agent risk perception and coping perception are important influences. Agent mitigation and community mitigation are interconnected, with higher agent mitigation generally resulting in lower community mitigation, and vice versa.

In general, community mitigation results in reduced future damage. However, in some simulations, community mitigation is followed by a flood event that exceeds the mitigation height, resulting in substantial damage. Model runs with community damage tend to have higher total damage than those without, and this can be attributed to high damage events triggering the community action.

In addition to analyzing evolving flood risk under historic climate conditions, three future climate scenarios were analyzed, a median, 10%, and 90% climate scenario. Under the median climate scenario, total damage was generally higher than under the historic scenario. However, in some cases, damage under the median scenario was actually lower than damage under the historic scenario as the higher flood elevations triggered higher agent risk perception values and additional agent and community mitigation. The 10% and 90% climate scenarios are somewhat extreme, but in both cases, individual and community action result in a decline in damages over time. In the 10% scenario, the decline is primarily due to agent mitigation, while in the 90% scenario, large increases in the vacancy rate occur in addition to mitigation measures. This makes sense, because in less severe flooding, a limited number of agents are impacted, and the problem can most efficiently be dealt with at the agent level. For more pronounced flooding, community level efforts make more sense. Under an extreme climate scenario with more frequent and severe floods, our model suggests that many individuals move out of the study area.

The use of an ABM for evolving flood risk allows for the relationship between flood events, individual action, and community action to be simulated. Individual action, including mitigation and movement in and out of high-risk areas, can have a significant influence on flood risk in a community. Furthermore, individuals are influenced by other individuals' experiences and actions, and this influence can also significantly affect how flood risk evolves. This was particularly evident in analysis of agent mitigation in the NB and LU-NB models. Due to the importance of both movement and neighbor interactions on community flood risk, future models should continue to incorporate both of these features, and potentially refine the behavioral and decision rules associated with these model aspects.

The primary limitation to the use of an ABM for this application is that assumptions and simplifications need to be developed regarding behavioral rules for individual and community action. In this study, these took the form of thresholds for individual risk and coping perception, required number of complaints and damage for community action, and probabilities of individuals moving into at-risk areas. Because of this limitation, an extensive sensitivity analysis was run on these parameters to understand the effect that changes in the assumptions has on the model results. In some cases the model results were sensitive to changes in these parameters, and in other cases they were not. In generating results for decision-making in a particular community, it would be important to include behavioral rules specific to that community, in addition to physical hazard information for that community.

This study was a prototype for the use of ABM in simulating evolving flood risk in a community. Future work will include a more in-depth study of the evolution of flood risk in Fargo, ND and Moorhead, MN, and potentially other locations. This will include surveys pertaining to individual and community flood risk perception and behavior, as well as detailed hydrologic and hydraulic modeling, and the use of additional downscaled future climate data. The results of this study provide useful insights into how community flood risk evolves and also provide an understanding of how model parameters influence model outcomes, lending insight into priorities for future work.

Chapter 5 Conclusion

Weather-related natural hazards result in significant property damage and loss of life. A better understanding of the risks associated with weather-related natural hazards can lead to more informed decision making regarding risk management and mitigation. This study focuses on risk from floods and hurricanes and the application of systems engineering methods to enhance the understanding of these risks. Risk associated with hurricanes and floods are many-faceted problems, and systems approaches can provide new insights and solutions. Two types of systems analysis approaches are used in this study: data analytics and agent-based modeling (ABM).

5.1 Summary and Contributions

5.1.1.Hurricane Isaac Power Outage Analysis

In August 2012, Hurricane Isaac, a Category 1 hurricane at landfall, caused extensive power outages in Louisiana. The storm brought high winds, storm surge and flooding to Louisiana, and power outages were widespread and prolonged. Hourly power outage data for the state of Louisiana was collected during the storm and analyzed. This analysis included correlation of hourly power outage figures by zip code with storm conditions including wind, rainfall, and storm surge using a non-parametric ensemble data mining approach. Results were analyzed to understand how correlation of power outages with storm conditions differed geographically within the state. This analysis provided insight on how rainfall and storm surge, along with wind, contribute to power outages in hurricanes. By conducting a longitudinal study of outages at the zip code level, we were able to gain insight into the causal drivers of power outages during hurricanes. Our analysis showed that the statistical importance of storm characteristic covariates to power outages varies geographically. For Hurricane Isaac, wind speed, precipitation, and previous outages generally had high importance, whereas storm surge had lower importance, even in zip codes that experienced significant surge. The results of this analysis can inform the development of power outage forecasting models, which often focus strictly on wind-related covariates. Our study of Hurricane Isaac indicates that inclusion of other covariates, particularly precipitation, may improve model accuracy and robustness across a range of storm conditions and geography.

5.1.2 Basin Characteristics as Risk Factors for Unexpected Flood Frequency

Flood frequency analysis is based on stream gage data with limited periods of record and uncertain analysis methods. For some gages, the estimated 100-year event is in good agreement with the gage record, while in other cases there are more or less 100-year events than expected. The goal of this work is to assess which, if any, basin characteristics are associated with situations in which the realized record of streamflow events would appear to be unlikely when judged against the results of a standard flood frequency analysis approach. The focus of this research is 100-year flood events, using the Mid-Atlantic region as a case study. 100-year flow rates for stream gages were estimated using Bulletin 17B methods, and the probability of the realized record for each gage was calculated. A Random Forest model of probability of outcome versus watershed characteristics was developed and used to understand which characteristics are associated with gages for which the realized record has a low likelihood probability of outcome when judged against Bulletin 17B results. Characteristics associated with lower probability outcomes included higher gage skew, larger drainage area, higher mean peak annual flow rate, moderate road-stream intersections, and lower percent forested and percent developed watershed area. A clustering analysis reinforced the findings of the Random Forest model. The results can be used to identify watersheds where advanced flood frequency methods may be warranted.

5.1.3 An Agent-Based Model of Evolving Community Flood Risk

Typically, flood risk models focus on simulation of the physical hazard and do not capture the impact of community policies and individual decisions on flood risk. Poorly planned or executed flood mitigation projects can have unanticipated consequences, and can even result in increased flooding and reduced public safety. Individual behavior, including the decision to implement mitigation, to move in or out of flood prone areas, and to purchase insurance, plays a major role in community flood risk. The purpose of this study is to improve the understanding of the temporal aspects of flood risk through a combined analysis of the behavioral, engineering, and physical aspects of flood risk. Additionally, the study presents a new modeling approach for integrating behavior, policy, flood hazards, and engineering interventions. This research improves the understanding of temporal changes in community flood risk through a combined analysis of the behavioral, engineering, and physical hazard components of flood risk. The hypothesis is that the interaction of policies, individual behavior, and flood mitigation measures can result in unanticipated changes to flood vulnerability that are not captured by standard engineering-based models.

In the ABM, the agents are households, modeled as land parcels. An annual maximum flood occurs in each year of the 50-year simulation period, and flood risk metrics are recorded annually. The agents can take individual action and can also influence community action. Each agent makes an annual decision about flood risk management actions, as does the community. Flood risk changes over time based on stochastic flood outcomes, individual action, and community action.

In general, community mitigation results in reduced future damage. However, in some simulations, community mitigation is followed by a flood event that exceeds the mitigation height, resulting in substantial damage. Under the median future climate scenario, total damage was generally higher than under the historic scenario. However, in some cases, damage under the median scenario was actually lower than damage under the historic scenario as the higher flood elevations triggered higher agent risk perception values and additional agent and community mitigation. The 10% and 90% future climate scenarios are somewhat extreme, but in both cases, individual and community action result in a decline in damages over time.

5.2 Final Remarks and Research Limitations

This work uses systems analysis methods to improve the understanding of risks from hurricanes and floods. Analysis of data from Hurricane Isaac shows that drivers of hurricane power outages vary geospatially in a storm and that outage forecasting models can be made more robust by including factors like precipitation in addition to standard wind variables. A study of flood frequency and probability of outcome in the Mid-Atlantic region uncovers basin characteristics for which low probability flood frequency outcomes may be more likely to occur. An ABM of evolving flood risk illustrates the role that individual behavior, community action, and climate change play in the evolution of flood risk in a community. While these studies each improve the understanding of various facets of natural hazard risk, each has its own limitations and future work can be targeted to address these limitations.

5.2.1 Hurricane Isaac Power Outage Analysis

The primary limitation of this work was the focus on one storm event in a single geographic location. The study was limited to power outages during Hurricane Isaac in the Entergy service area in Louisiana. Other storms and geographic areas may generate different results. While the results of this study found precipitation and wind to be key drivers of power outages at locations in Louisiana during Hurricane Isaac, different outcomes might occur with a different storm and/or location. Additionally, this study was limited to certain major weather drivers including wind, precipitation, and storm surge. Other meteorological and geographical variables could also be significantly correlated with power outages. This could include variables such as soil moisture levels, land use data, topographic data, and power system data (Nateghi et al. 2013). Future work could include repeating this analysis for additional hurricanes in Louisiana, as well as analyzing other geographic areas.

5.2.2 Basin Characteristics as Risk Factors for Unexpected Flood Frequency

The analysis of basin characteristics as risk factors for response variable involved a novel approach and provided insight into characteristics that are correlated with low probability flood frequency outcomes. However, there are several key limitations of this study associated with the scope, the data set, and the model accuracy.

This study included only stream gages located in the Mid-Atlantic region. The results may not be applicable to other regions due to different streamflow generating mechanisms associated with different weather patterns, land cover, soils, and topography. Furthermore, the analysis focused solely on one flood frequency analysis method, Bulletin 17B. The results would likely differ for other flood frequency analysis methods, including the pending Bulletin 17C method. In the future, the approach used in this study could be applied to other geographic regions and flood frequency analysis methods for comparison purposes.

Another limitation, which is common to most flood frequency analysis studies, is limited stream gage data. This study focused on 100-year events, while the stream gage data had periods of record as low as 40 years. The differing periods of record for the gages used in the study could have had an impact on the accuracy and validity of the model. Efforts to account for this limitation were made, in the form of analysis of a bootstrapped data set.

The choice of response variable, as well as model accuracy, are additional limitations of this study. There was no obvious choice of response variable for use in analyzing unexpected flood frequency outcomes. We chose to use probability of outcome, and other possible choices would be the number of 100-year or greater events, ratio of actual to expected 100-year events, or deviation from the expected number of 100-year events. However, each of these choices involves limitations, and the probability of outcome was chosen as the most suitable option for the purposes of this study. Furthermore, the Random Forest model accuracy was limited. This was to be expected, since flood frequency is impacted by factors not included in this study, particularly meteorological events.

5.2.3 An ABM of Evolving Flood Risk

The key limitation of the ABM of evolving flood risk involved the quantification of behavioral rules. In the literature regarding individual behavior and flood risk, there was much qualitative description of factors that influence an individual's likelihood to take action to mitigate risk. However, quantitative information about these factors was very limited. The behavioral model generated for this study makes a number of assumptions in order to develop equations to estimate an individual's risk perception, coping perception, and decision on taking action. This model provides a good framework and generally captures the key factors that would influence an agent's decision-making process. In order to develop a behavioral model that is specific to a community and the individuals living there, and more precisely quantifies individual perceptions and actions, a more in-depth behavioral study would be required.

This study was meant to serve as an experiment of the modeling methodology and a prototype for future work, and as a result, the model may not accurately represent the case study area that was used. Some basic assumptions about the agents, represented as land parcels, were made. It was assumed that the highest elevation on the land parcel is equivalent to the first floor elevation of the structure. It was assumed that the property value is an adequate representation of the socioeconomic factors that would influence an agent's coping perception. For purposes of the utility calculation used in an agent's decision of whether or not to mitigate, it was assumed that the cost of elevating equipment or a structure were the same for all agents. All parcels were treated as individual agents, regardless of the number of people that might be living on a given parcel. More fundamentally, it was assumed that no individual or community mitigation was completed in the Fargo case study area prior to the simulation. This assumption does not match the physical reality of the community, where levees are currently in place and are being improved and expanded.

The ABM neighbor models represented all parcels in the case study area as neighbors to each other. In a small area such as the case study area, it is quite likely that all agents could influence other agents through their mitigation action. However, there are more specific ways to simulate agent interactions in an ABM. Parcel adjacency or a radial distance could be used to specify which agents are neighbors to each other. This type of neighbor specification could produce results that more realistically illustrate the geospatial patterns of neighbor influence. Future simulations should consider using other neighbor identification methods for a higher level of precision.

Only one community mitigation alternative was considered in this study. Levees were chosen as the method due to their prevalence, including in the Fargo area. For simplicity, it was assumed that the flood mitigation measure implemented in the simulation would not be breached, while the area behind the levee could be inundated by flood events that exceed the levee height. Other flood mitigation methods could be incorporated into future work, like a flood diversion project such as the one that is currently proposed by the USACE for the Fargo area. Green or natural flood mitigation alternatives could also be simulated, and the interplay between these types of mitigation measures and individual behavior could be quite interesting. This study did not focus heavily on the implications of community flood management policies, such as land use regulation and subsidies, but these could certainly be incorporated into future work. The influence of flood insurance was also not included. Flood insurance and the regulatory policies that go along with flood insurance have a key influence on both individual and community level behavior, and should be considered in future work.

In this study, climate change was simulated in the form of future climate scenarios. This provided some interesting insights into how flood risk might evolve differently in a climate with higher or lower magnitude flooding. In reality, climate change is occurring gradually, and individual and community behavior will likely change gradually over time in response to climate change. Future work could involve phasing in changes to the potential magnitudes of annual floods for a more realistic simulation. The method of developing climate scenarios for this study, involving percentage changes to the set of flood elevations sampled from in the simulation, was somewhat simplistic, though complex enough for the purposes of this study. Future work could include more thorough models of hydrology and hydraulics and the potential effects of climate change.

Appendix A Full list of Model Covariates

Table A-1: List of Model Covariates

Covariate	Abbreviation	Units	Included in RF4
Drainage Area	DRAIN_SQKM	square kilometers	Yes
Hydrologic Disturbance Index	HYDRO_DISTURB_INDX	unitless	Yes
Watershed compactness ratio	BAS_COMPACTNESS	unitless	Yes
Mean annual Precipitation for the basin	PPTAVG_BASIN	centimeters	Yes
Average annual air temperature for the watershed	T_AVG_BASIN	degrees C	Yes
Average monthly maximum air temperature	T_MAX_BASIN	degrees C	No
Watershed average number of days of measurable precipitation (based on 30 year average)	WD_BASIN	days	Yes
Site average number of days of measurable precipitation (based on 30 year average)	WD_SITE	days	No
Watershed average of monthly maximum number of days of measureable precipitation	WDMAX_BASIN	days	No
Watershed average of monthly minimum number of days of measureable precipitation	WDMIN_BASIN	days	No
Site average of monthly maximum number of days of measureable precipitation	WDMAX_SITE	days	No
Site average of monthly minimum number of days of measureable precipitation	WDMIN_SITE	days	No
Maximum Strahler stream order in watershed	STRAHLER_MAX	unitless	Yes
Sinuosity of main stream line	MAINSTEM_SINUOUSITY	unitless	Yes
Percent of mainstem stream(s) coded as artificial path in NHDPlus	ARTIFPATH_MAINSTEM_PCT	Percent	Yes
Percent of watershed area covered by lakes/ponds and reservoirs	HIRES_LENTIC_PCT	percent	Yes
Base flow index	BFI_AVE	percent	Yes
Dunne overland flow	PERDUN	Percentage of total streamflow	Yes
Horton overland flow	PERHOR	Percentage of total streamflow	Yes
Topographic wetness index	TOPWET	ln(meters)	Yes
Estimated average annual watershed runoff	RUNAVE7100	mm/year	Yes

APPENDIX A FULL LIST OF MODEL COVARIATES

Covariate	Abbreviation	Units	Included in RF4
Percent of watershed stream lengths which are first order streams	PCT_1ST_ORDER	percent	Yes
Percent of watershed stream lengths which are second order streams	PCT_2ND_ORDER	percent	Yes
Dam density (2009)	DDENS_2009	number of dams/100 km sq	Yes
Major dam density (2009)	MAJ_DDENS_2009	Number of major dams/100 km sq	No
Fragmentation Index of undeveloped land in the watershed	FRAGUN_BASIN	unitless	Yes
Watershed percent developed, 2006	DEVNLCD06	Percent	Yes
Watershed percent forest, 2006	FORESTNLCD06	Percent	Yes
Watershed percent agriculture, 2006	PLANTNLCD06	Percent	Yes
Watershed percent open water, 2006	WATERNLCD06	Percent	Yes
Mainstem 100 m buffer developed	MAINS100_DEV	Percent	No
Mainstem 100 m buffer forest area	MAINS100_FOREST	Percent	No
Mainstem 100 m buffer planted/cultivated (agricultural) area	MAINS100_PLANT	Percent	No
Mainstem 100 m buffer open water area	MAINS100_11	Percent	No
Mainstem 800 m buffer developed area	MAINS800_DEV	Percent	No
Mainstem 800 m buffer forest area	MAINS800_FOREST	Percent	No
Mainstem 800 m buffer agricultural area	MAINS800_PLANT	Percent	No
Mainstem 800 m buffer open water area	MAINS800_11	Percent	No
Riparian 100 m buffer developed area	RIP100_DEV	Percent	No
Riparian 100 m buffer forested area	RIP100_FOREST	Percent	No
Riparian 100 m buffer agricultural area	RIP100_PLANT	Percent	No
Riparian 100 m buffer open water area	RIP100_11	Percent	No
Riparian 800 m buffer developed area	RIP800_DEV	Percent	No
Riparian 800 m buffer forested area	RIP800_FOREST	Percent	No
Riparian 800 m buffer agricultural area	RIP800_PLANT	Percent	No

APPENDIX A FULL LIST OF MODEL COVARIATES

Covariate	Abbreviation	Units	Included in RF4
Riparian 800 m buffer open water area	RIP800_11	Percent	No
Population density in the watershed (2000)	PDEN_2000_BLOCK	Persons/sq km	Yes
Road density	ROADS_KM_SQ_KM	km/sq km	No
Number of road/stream intersections	RD_STR_INTERS	Number of intersections/km of stream length	Yes
Watershed percent impervious	IMPNLCD06	Percent	Yes
Percentage of soils in hydrologic group A	HGA	Percent	Yes
Percentage of soils in group A/D	HGAD	Percent	No
Percentage of soils in group D	HGD	Percent	Yes
Percentage of soils in group C/D	HGCD	Percent	No
Mean watershed elevation	ELEV_MEAN_M_BASIN	Meters	No
Elevation at gage location	ELEV_SITE_M	Meters	Yes
Elevation-relief ratio	RRMEAN	unitless	Yes
Mean watershed slope	SLOPE_PCT	percent	Yes
Aspect northness (range -1 to 1 with 1 meaning watershed faces/drains due north and -1 means due south)	ASPECT_NORTHNESS	Unitless	Yes
Aspect eastness (range -1 to 1 with 1 meaning watershed faces/drains due east and -1 means due west)	ASPECT_EASTNESS	unitless	Yes

Appendix B Sensitivity Analysis for Flood Risk ABM

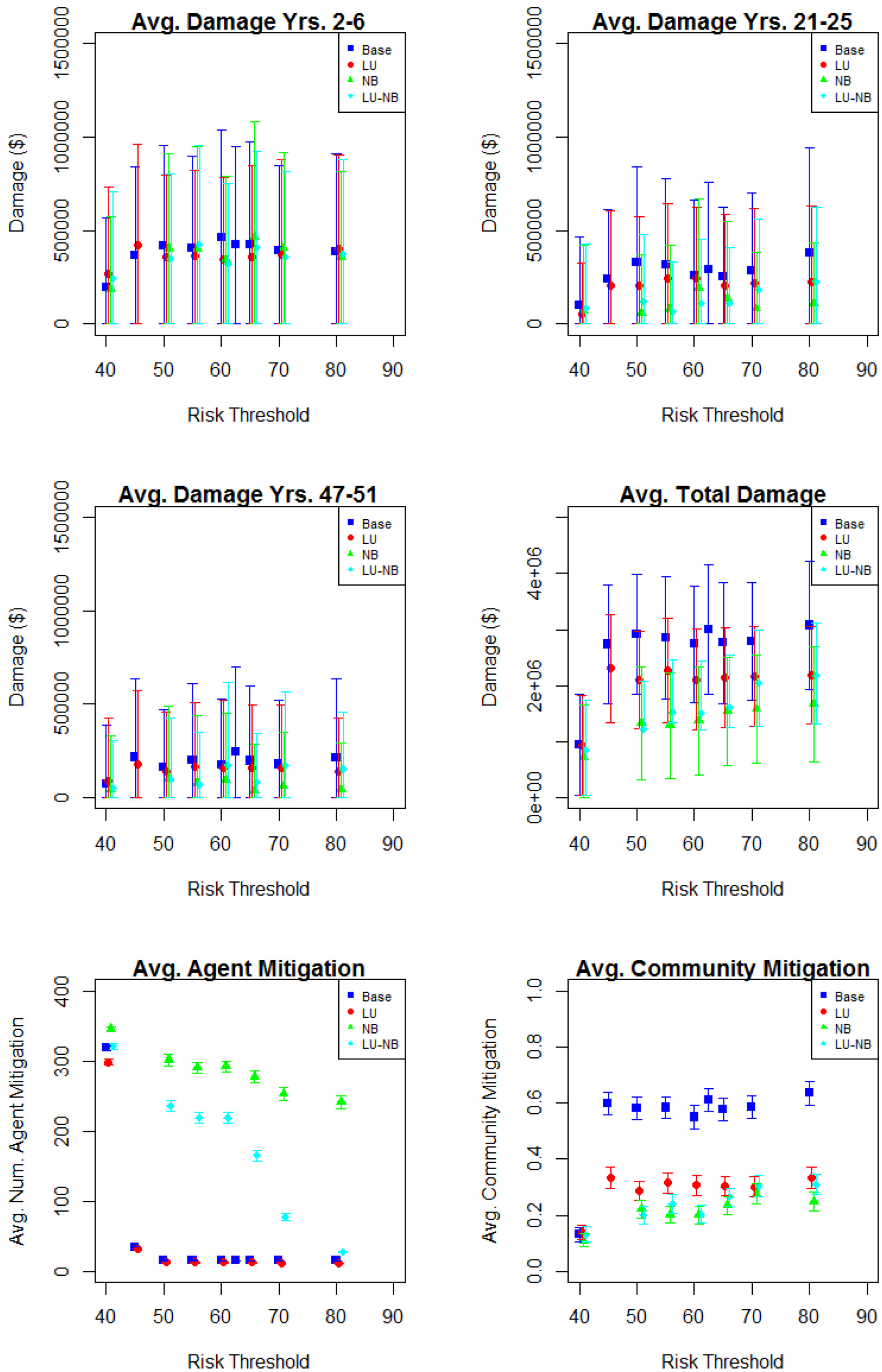

Figure B-1: Sensitivity analysis for risk threshold

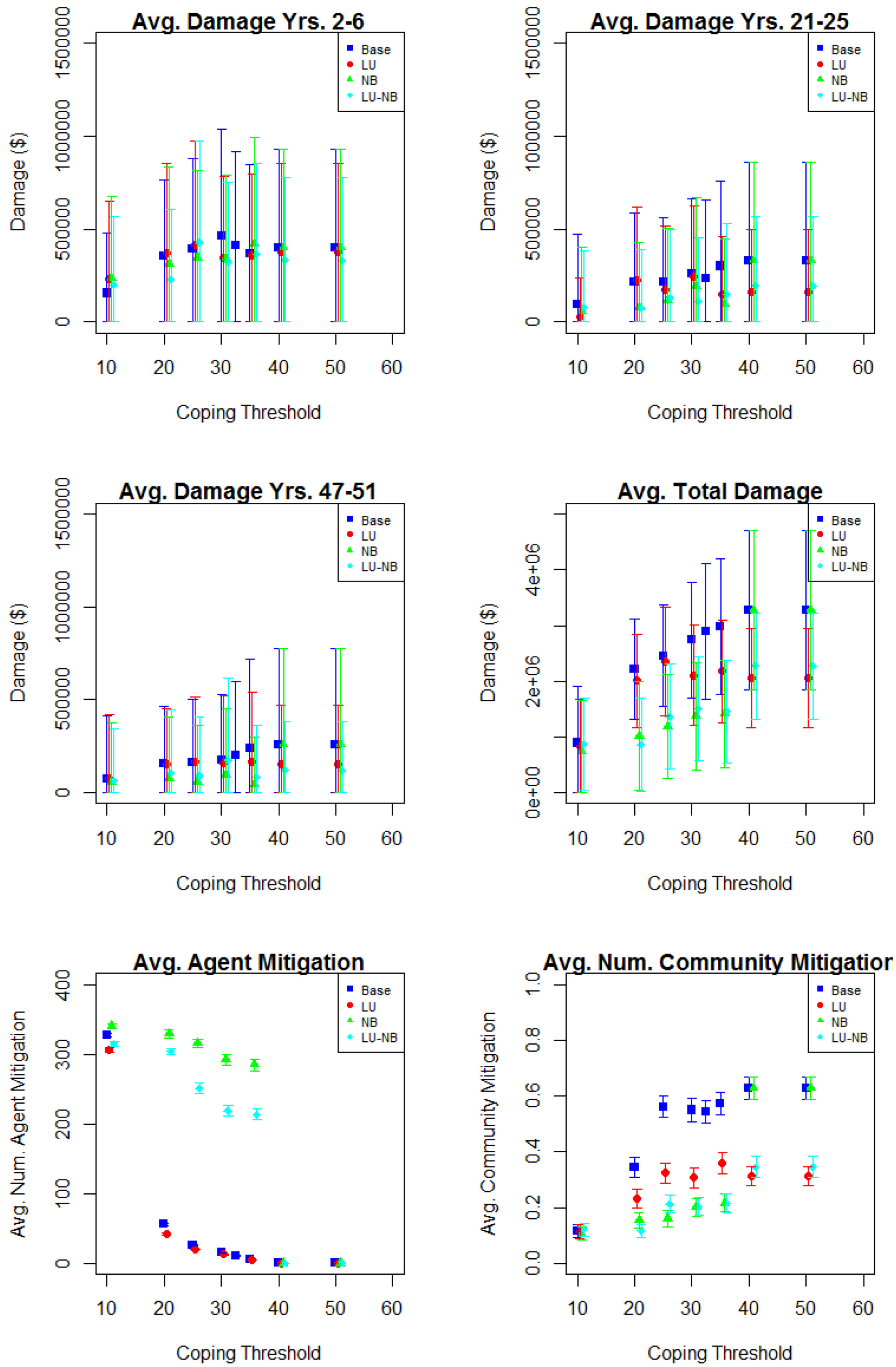

Figure B-2: Sensitivity analysis for coping threshold

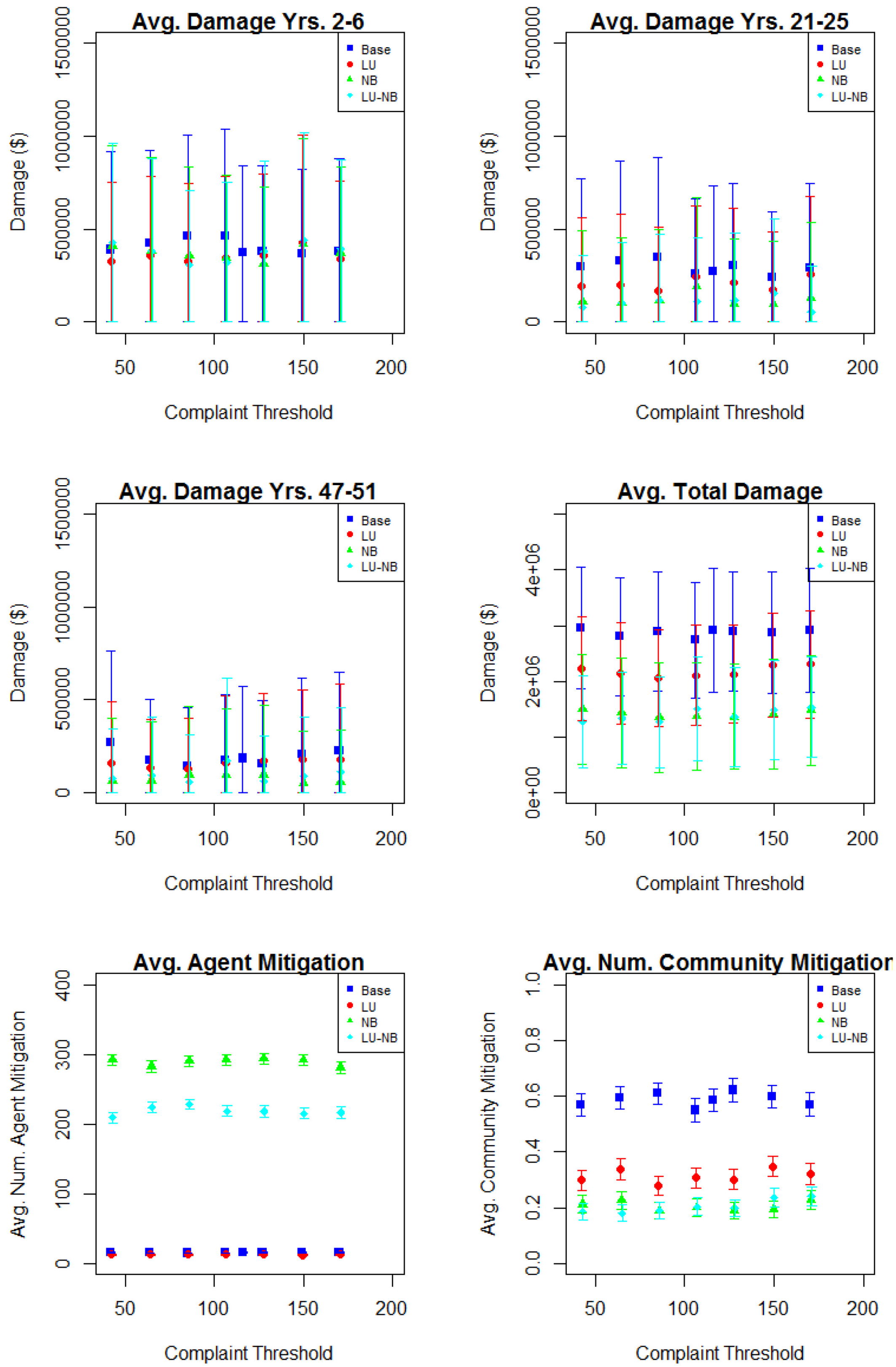

Figure B-3: Sensitivity analysis for complaint threshold

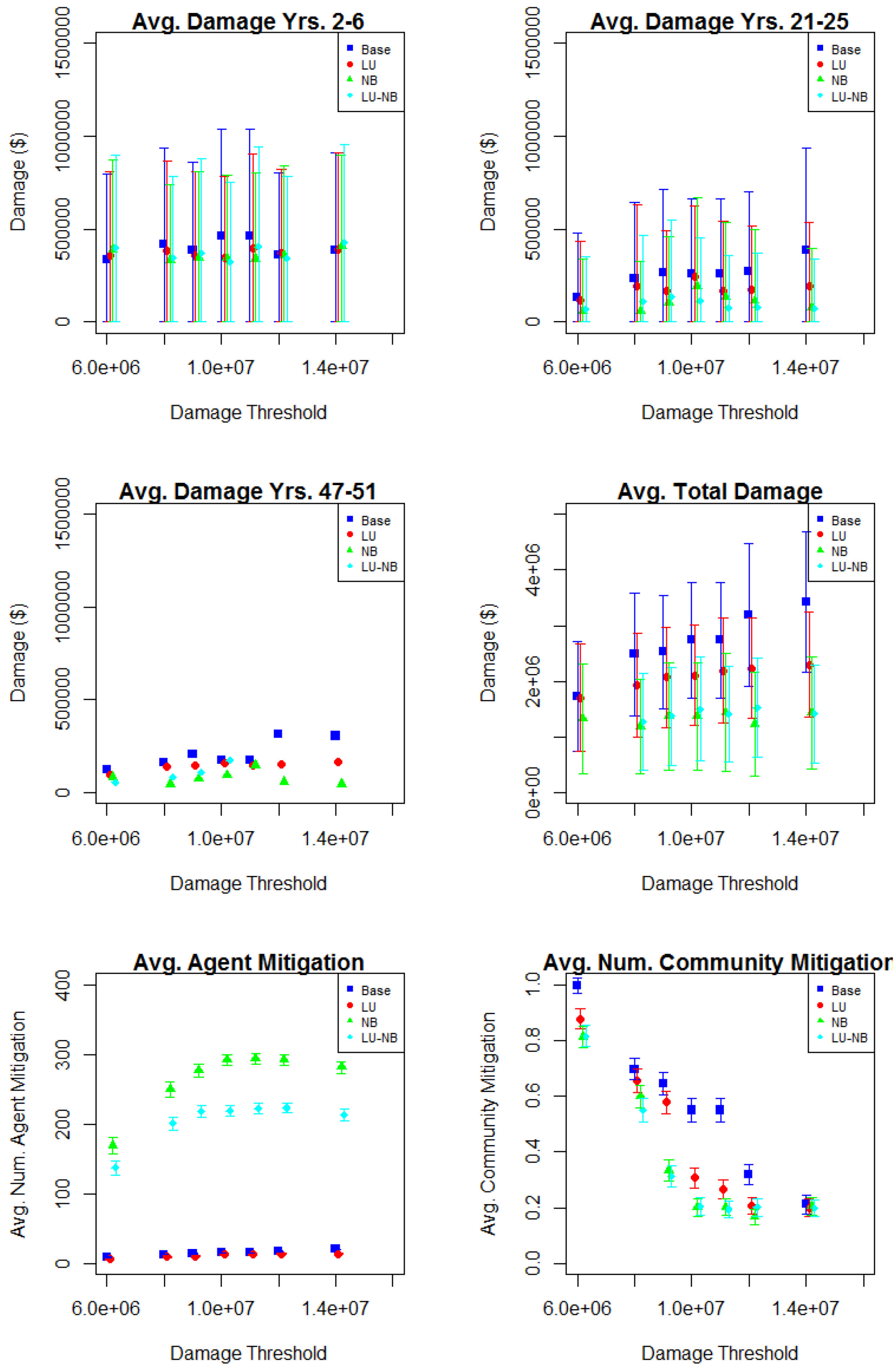

Figure B-4: Sensitivity Analysis for damage threshold

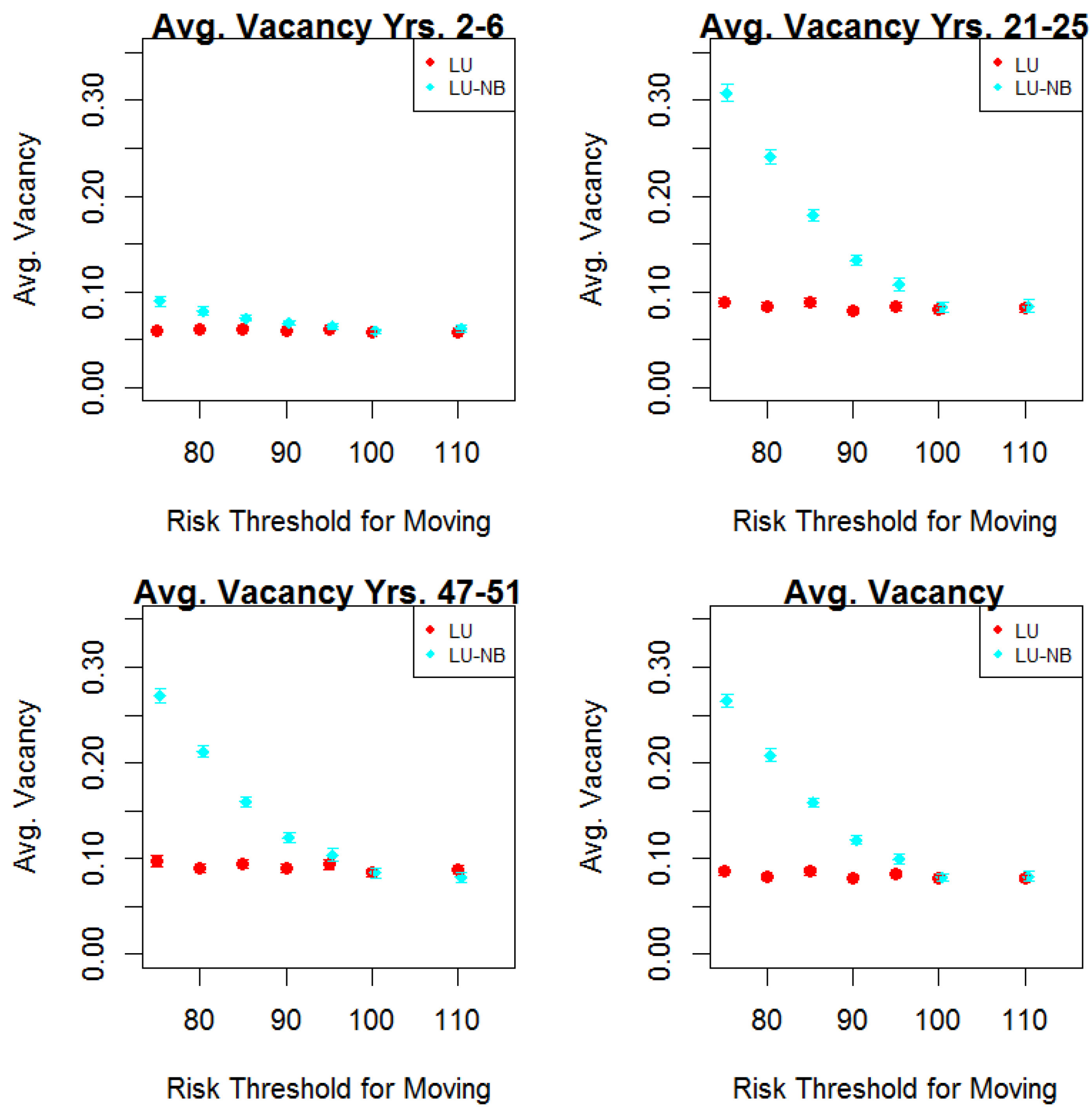

Figure B-5: Sensitivity analysis for risk threshold for moving

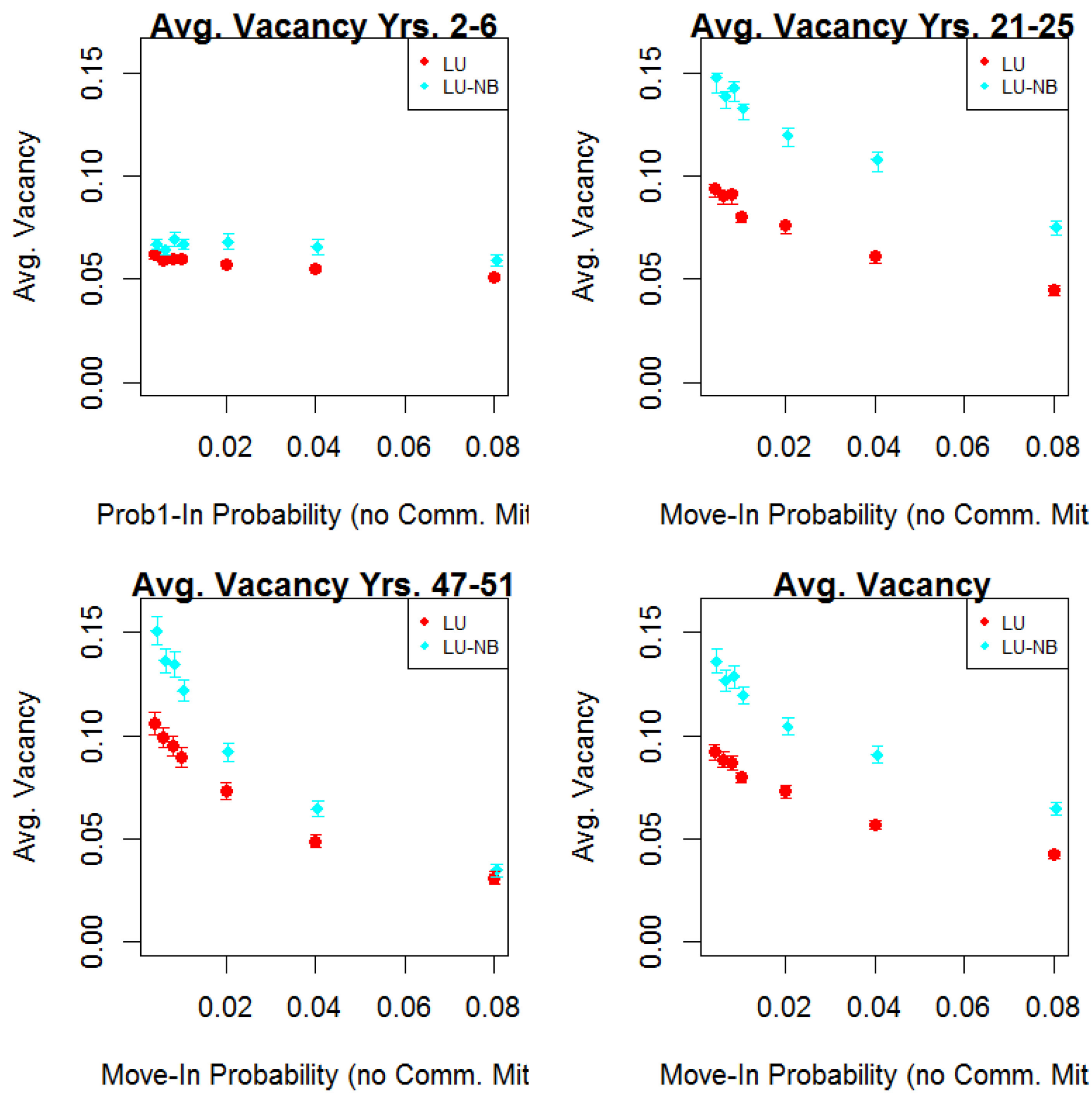

Figure B-6: Sensitivity analysis for probability of moving in (without community mitigation)

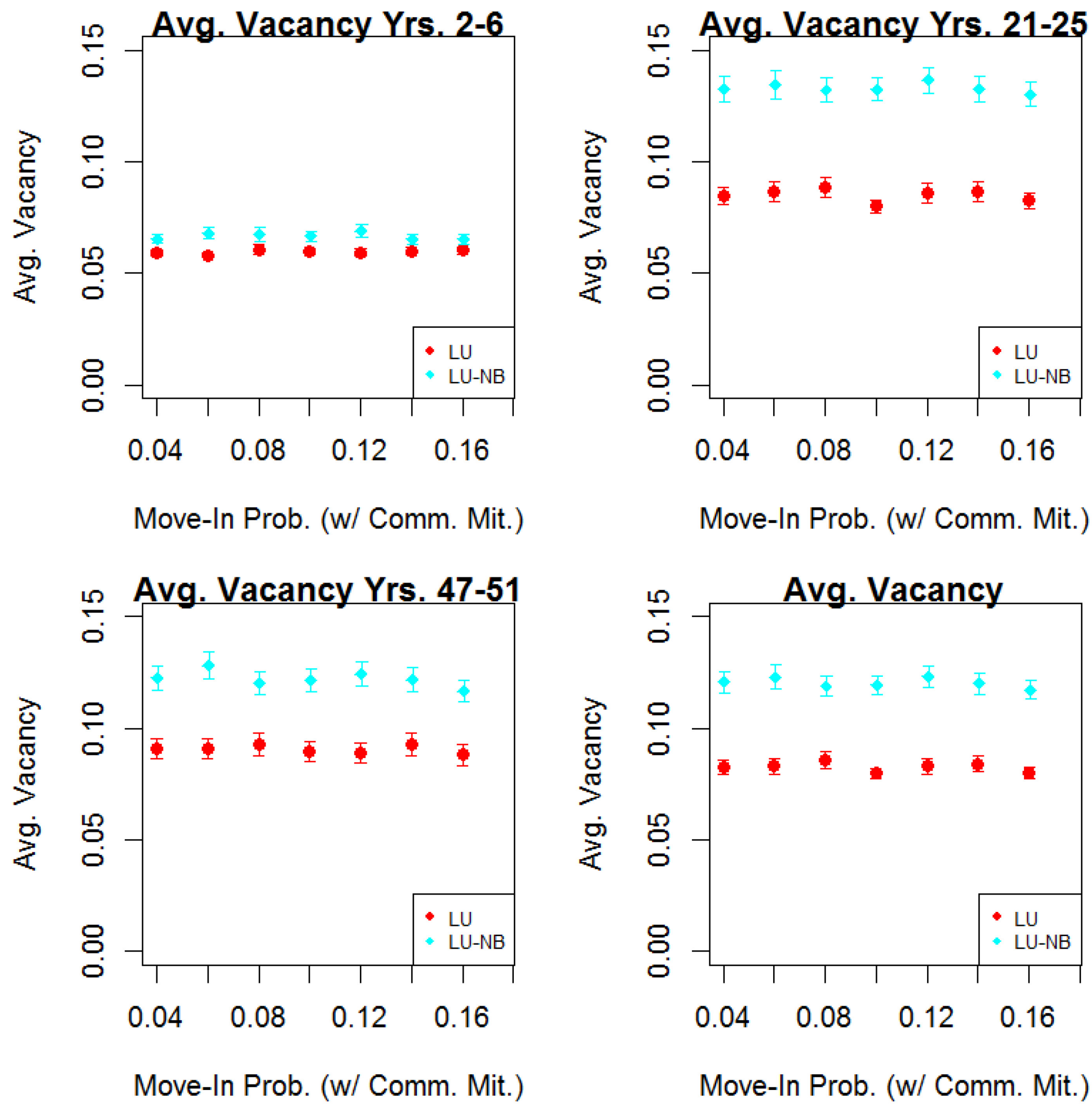

Figure B-7: Sensitivity analysis for probability of moving in (with community mitigation)

Appendix C Sensitivity Analysis for Flood Risk ABM, Future Climate Scenarios

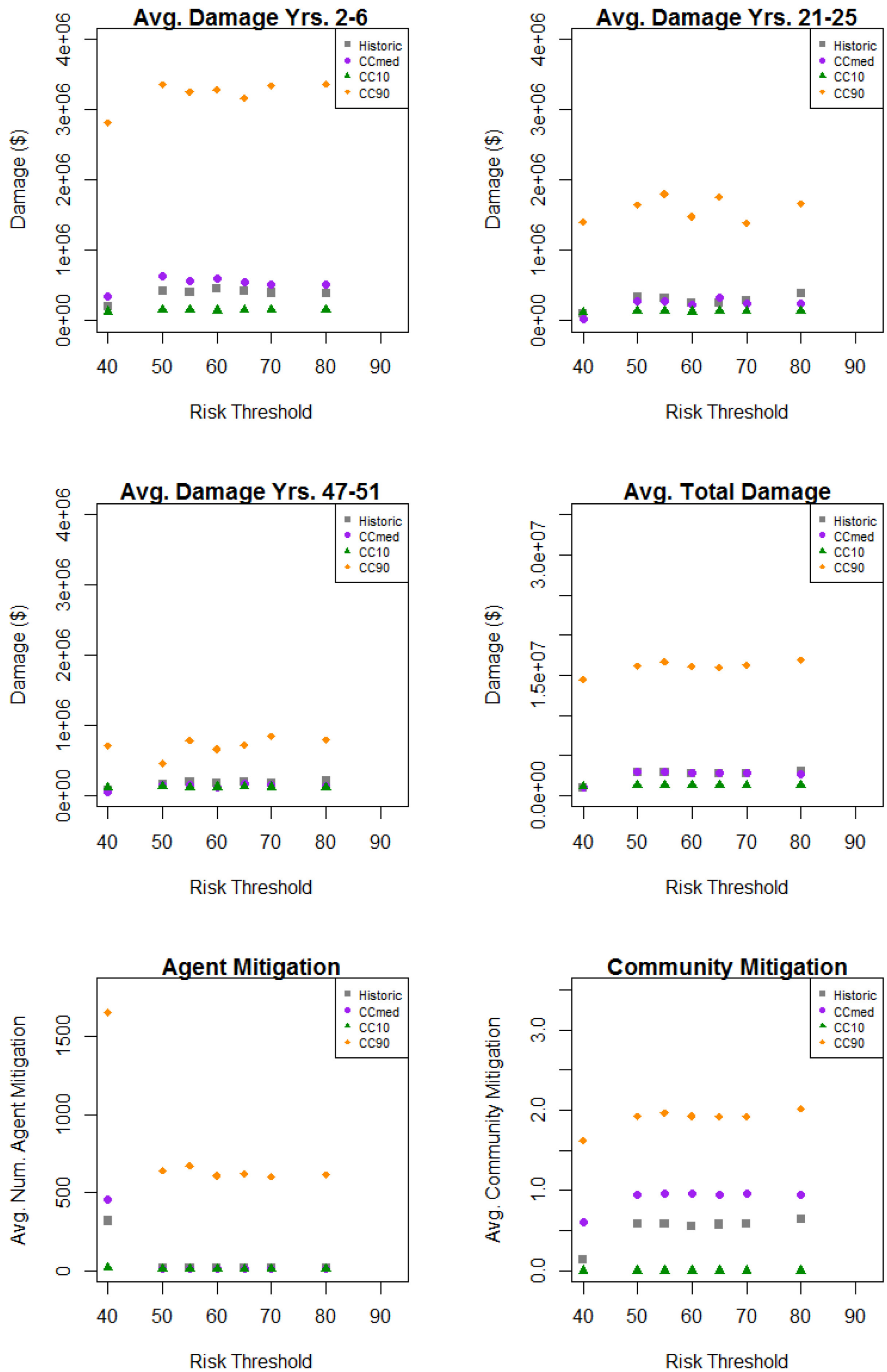

Figure C-1: Sensitivity analysis for risk threshold, Base model, climate change scenarios

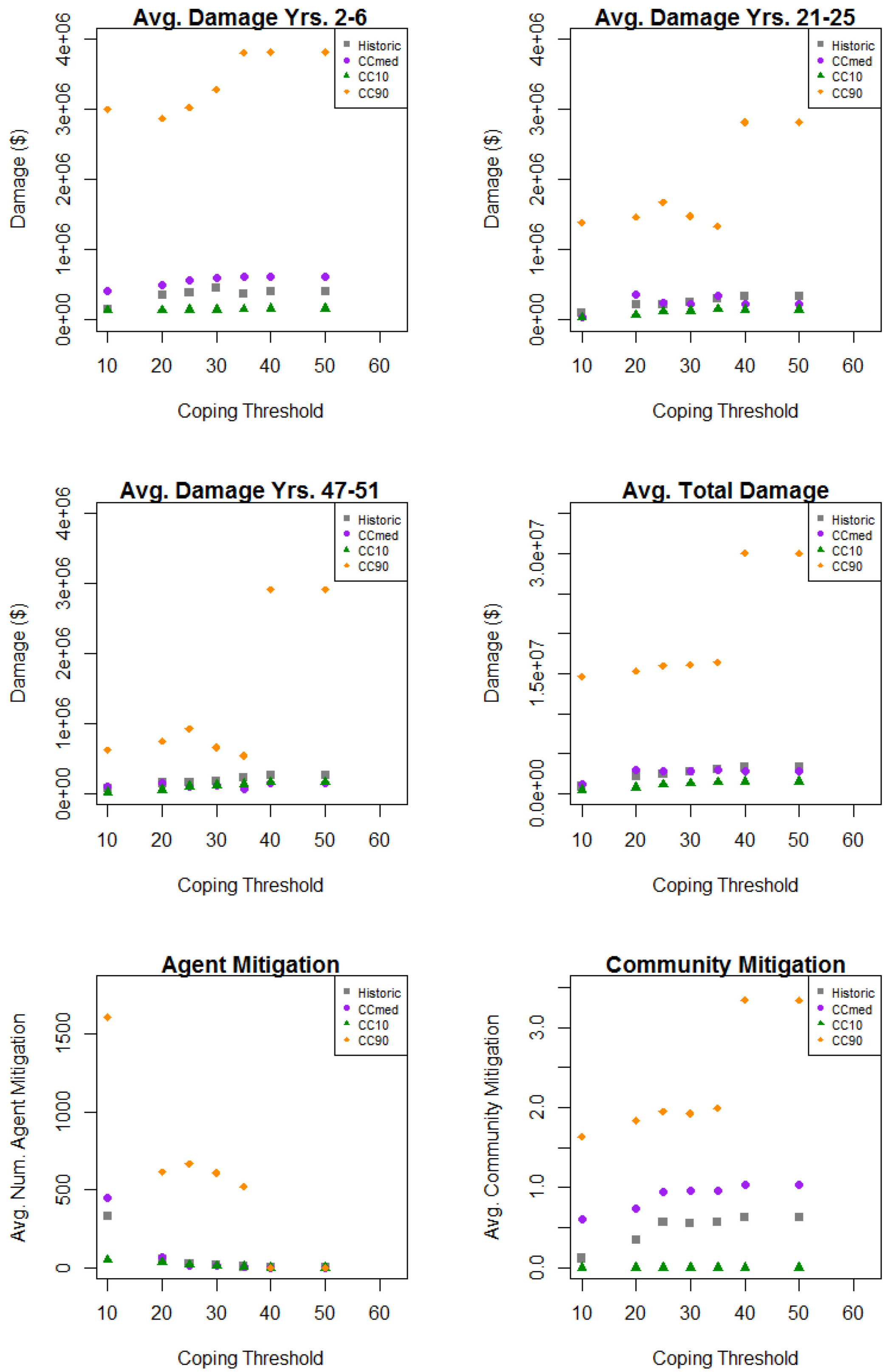

Figure C-2: Sensitivity analysis for coping threshold, Base model, climate change scenarios

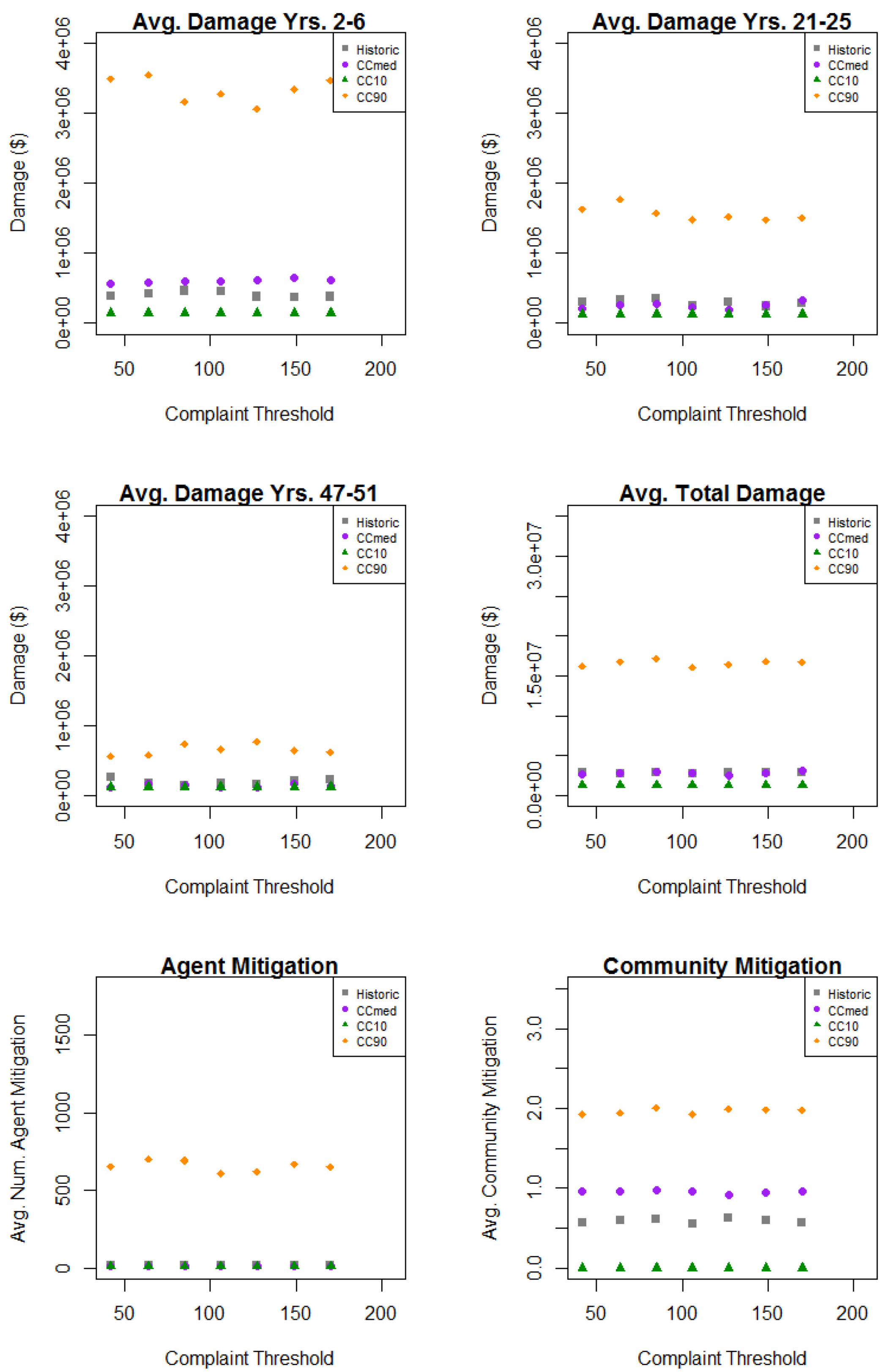

Figure C-3: Sensitivity analysis for complaint threshold, Base model climate change scenarios

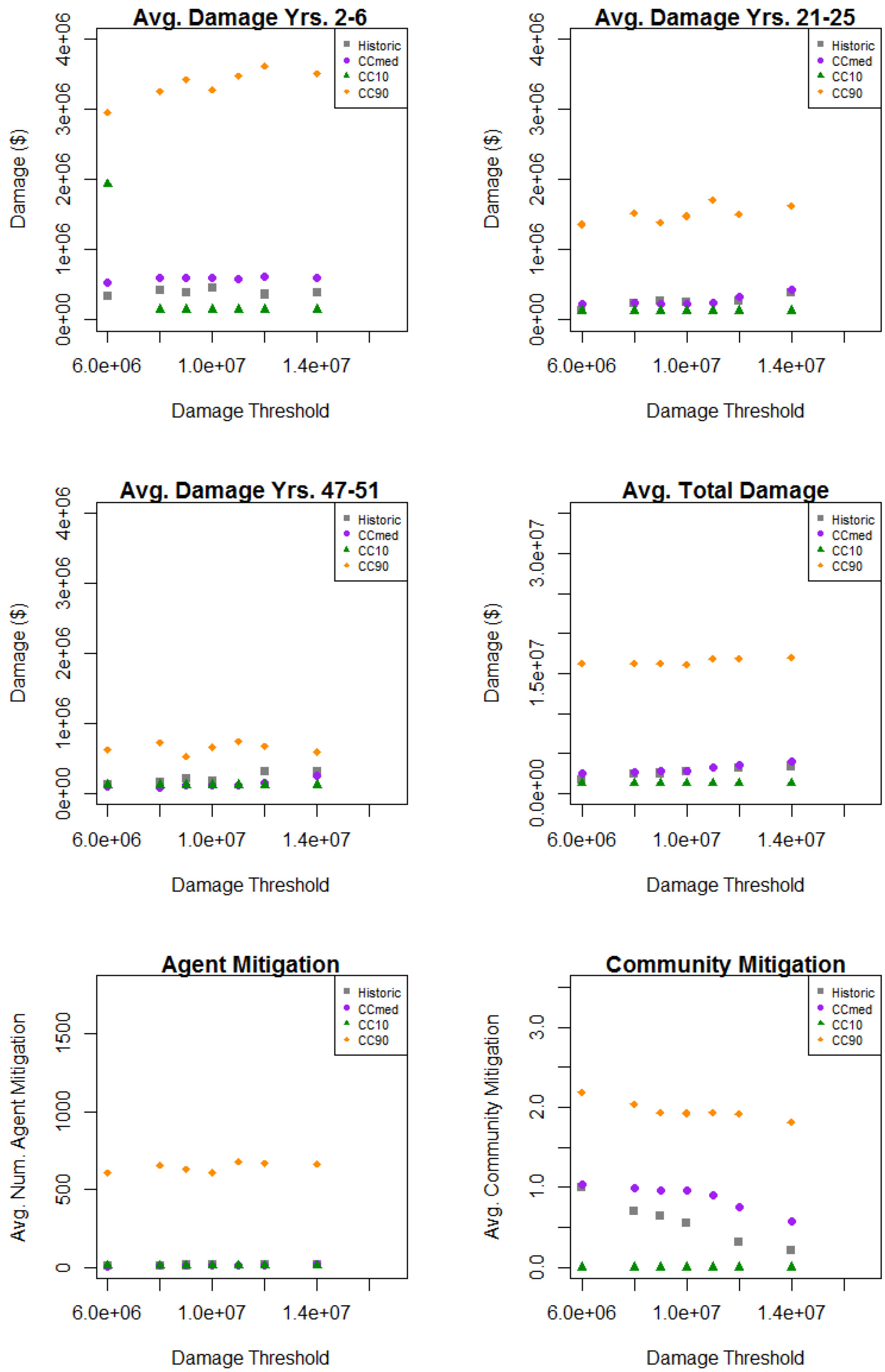

Figure C-4: Sensitivity analysis for damage threshold, Base model, climate change scenarios

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Vita

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